

Emissions and Economics of Behind-the-Meter Electricity Storage

Michael J. Fisher^{*†} and *Jay Apt*^{†,‡}

[†] Department of Engineering & Public Policy, Carnegie Mellon University, 5000 Forbes Avenue,
Pittsburgh, Pennsylvania 15213, United States

[‡] Tepper School of Business, Carnegie Mellon University, 5000 Forbes Avenue, Pittsburgh,
Pennsylvania 15213, United States

ABSTRACT: Annual installations of behind-the-meter (BTM) electric storage capacity are forecast to eclipse grid-side electrochemical storage by the end of the decade. Here we characterize the economic payoff and regional emission consequences of BTM storage under different tariff conditions, battery characteristics, and ownership scenarios, using metered load for several hundred commercial and industrial customers. Net emissions are calculated as increased system emissions from charging minus avoided emissions from discharging. Net CO₂ emissions range from 75 to 270 kg/MWh of delivered energy depending on location and ownership perspective, though in New York these emissions can be reduced with careful tariff design. Net NO_x emissions range from -0.13 to 0.24 kg/MWh and net SO₂ emissions range from -0.01 to 0.58 kg/MWh. Emission rates are driven primarily by energy losses, not by the difference between marginal emission rates during battery charging and discharging. Economics are favorable for many buildings in high cost regions like California and New York, even without subsidies. Future penetration into average cost regions like Pennsylvania will depend greatly on cost reductions and wholesale prices for ancillary services.

■ INTRODUCTION

Stationary electrochemical (battery) storage has seen significant improvements in cost in the last decade and is a promising way to perform many electric grid functions.^{1,2} Battery storage is being installed both on the utility side of the customer meter at the transmission/distribution level (“grid-scale”), and at individual building sites, or “behind-the-meter” (BTM). Grid-scale storage can be used to delay infrastructure upgrades, perform wholesale market transactions including energy price arbitrage and frequency regulation, and absorb over-generation by distributed generation resources, among other services. BTM batteries can be used to decrease a customer’s energy costs by shifting the timing of utility purchases (demand charge reduction) or aggregated with other batteries to provide wholesale services to the grid. BTM storage is being adopted in areas that have high retail electricity prices and generous battery subsidies. BTM storage capacity is expected to double each year through 2019 in the U.S., when it will represent almost half (~400MW) of annual storage installations by capacity.³

Storage has been viewed as a solution for a more sustainable power system because it can smooth intermittent renewable generation.⁴ Policy makers are now implementing rules and subsidies that encourage large scale deployments of electric storage. California has set a storage procurement target of 1.3GW by 2020⁵ and provided an incentive of \$1,300/kW.⁶ New York City has an incentive of \$2,100/kW.⁷ At the federal level, FERC Order 755⁸ instructed grid operators to compensate fast-responding resources like storage in frequency regulation markets for their speed and accuracy.

A number of studies have shown that grid-scale storage will increase total power system emissions,⁹⁻¹³ even in the Texas system that contains a relatively high penetration of natural gas and renewables.¹⁴ Many of these studies focus on energy arbitrage where batteries shift power

from high cost periods (evening) to low cost periods (overnight). In most regions of the U.S., this use pattern will result in shifting generation from natural gas to coal⁹ and in all regions more power is used, since storage has a round-trip efficiency that is less than 100%.

The emissions consequences of deploying a storage technology depends in part on how it is operated; in turn the operating policies depend on who owns the storage. Previous research has focused on grid-scale storage. Investor-owned grid-scale batteries will be operated to maximize profit from wholesale market transactions, resulting in homogenous battery behavior across a grid region. The operation of BTM batteries is more heterogeneous because profit maximizing behavior will depend on the interaction between the load profile of the building, rate structures (these vary widely among utility service territories), and possible wholesale market transactions.

Very little work has been done to investigate the behavior and grid-level consequences of a large deployment of BTM batteries. Neubauer and Simpson¹⁵ used the National Renewable Energy Laboratory's (NREL) BLAST¹⁶ model to study the behavior of a fleet of BTM batteries, but the work used load data from only 98 commercial buildings, used only one utility tariff scenario, did not consider ancillary services, and did not calculate emissions effects.

Our analysis focuses on the operation of commercial and industrial (C&I) BTM storage under several market and tariff conditions and across ownership scenarios in order to characterize economics and net emissions. C&I is important because recent data suggest the storage capacity installed in this segment has outstripped residential installations by an order of magnitude.³ The goal of our work is to understand the economic conditions under which BTM storage will experience rapid adoption, the effects on system emissions, and alternative incentive structures that might mitigate those environmental effects.

▪ MATERIALS AND METHODS

Battery Optimization Model. In this section we describe the model and its parameters, objective function and constraints in general terms. The mathematical formulation, a more detailed discussion of each equation, and the computational implementation can be found in the Supporting Information (SI). Each individual building in our dataset is given a simulated battery. We assume a lithium-ion phosphate chemistry currently used by SonnenBatterie.¹⁷ Other lithium-ion chemistries have similar operational performance but are more sensitive to degradation from large swings in battery state-of-charge. We formulate a linear programming problem to minimize energy costs and maximize revenue to the battery owner over the course of 1 year. Depending on the ownership perspective, the battery is able to perform energy arbitrage, reduce demand charges, and/or provide frequency regulation and spinning reserve. The optimization is conducted at 15-minute intervals to reflect the typical structure of demand charges and the sampling rate of many meters. We assume that the storage system is too small to affect market prices or marginal system emissions.

Battery characteristics, such as capacity (kW), duration of discharge (hours), cost (\$/kWh and \$/kW), and round-trip efficiency (%) were fixed at the following values for the base case results. A full sensitivity analysis is given in the SI. Battery capacity was sized to 20% of the building's peak load (sensitivity: 15%-25%) in increments of 18kW, the smallest SonnenBatterie unit.¹⁸ For some buildings the coefficient of variation of load was low and sizing to peak load would drastically oversize the battery; these batteries were sized to be no greater than 50% of the total annual range of load, reducing the weighted average battery size across the sample to 17% of peak load. Visibility into current installation costs for power and energy subsystems is low; assumed capital costs of \$600/kWh + \$400/kW are taken from a 2011 Sandia National

Laboratory report¹⁹ (sensitivity: 33%-100% of base case). These values match well to recently reported total system costs of ~\$750/kWh for a 2-hour duration Tesla’s Powerpack²⁰ and are in line with ranges used in the battery literature.^{21,22} A 1 hour duration was chosen in our base case results because it exhibited a favorable tradeoff between cost and revenue, though we also show results for 0.5 – 4 hour durations. Round-trip efficiency was assumed to be 83%²³ (sensitivity: 83%-91%).

The economic incentives facing the battery owner will affect battery operations. In addition to a wholesale-only market participant and individual customer facing retail rates, an “aggregator” can pool retail resources for participation in wholesale markets. We examine all three ownership perspectives (customer, aggregator and wholesale-only) by varying the components of the objective function (**Table 1**) and constraints. BTM batteries would not be used solely for wholesale services, but the perspective is useful in benchmarking the performance of aggregator-owned batteries. All perspectives consider the economic tradeoff between battery use and degradation by multiplying the fraction of total lifetime energy used against the estimated replacement cost of the battery. We do not account for the physical effects of degradation on charge capacity, which California estimates at 1% per year.²⁴

Table 1. Components of Total Energy Cost Minimization

Perspective	Customer Energy Cost	Customer Demand Charge	Wholesale Energy Cost	Frequency Regulation Revenue	Spinning Reserve Revenue	Battery Degradation
Customer	✓	✓				✓
Aggregator	✓	✓	✓	✓	✓	✓
Wholesale			✓	✓	✓	✓

We also vary the amount of information available to the battery owner. Accurate forecasting of future building load and market clearing prices is central to the battery's ability to minimize energy costs. The optimization routines run by battery software are proprietary and sophisticated. We bound this real world scenario by assuming two different forecast scenarios: a perfect forecast and a persistence forecast that makes a rolling-horizon prediction using the average of historical data. An experienced trader is likely to perform better than the persistence forecast, but not as well as the perfect forecast. The persistence forecast scenarios were run on the Bridges Supercomputer at the Pittsburgh Supercomputing Center.²⁵ The perfect information scenarios were run on a 12-core Intel Xeon E5-2680 desktop machine.

The simulated battery faces three main types of physical and market constraints.

1. Battery state of charge (SOC) – Expressed as a fraction of total charge carrying capacity, SOC is restricted to a range between 20% and 100%, with a penalty function above 90%, to prevent increased degradation from high/low voltages. These restrictions are also found on electric vehicle batteries.²⁶
2. Total capacity – the capacity used to charge/discharge the battery and held for ancillary services cannot be greater than the capacity of the battery.
3. Frequency regulation capacity – we assume that the frequency regulation signal is energy neutral (no net charging or discharging), similar to the dynamic regulation signal implemented in the PJM Interconnection (PJM).²⁷ But *during* any given time period, the battery will gain and lose charge as it follows the regulation signal. Therefore, we place a constraint on capacity used for frequency regulation ensuring SOC limits are not violated while providing this service. We use one year of regulation signal from PJM to estimate the amount of charging/discharging possible during a single period.

Data. Load Data. Individually metered whole-building data are necessary to understand BTM battery storage behavior because brief load peaks can set monthly demand charges – these peaks would be smoothed out in averaged data. A utility in the Carolinas provided energy usage (kWh) data from 994 individual C&I meters at a 15-minute sample rate for 1 calendar year (2013). According to the utility, none of the customers had behind-the-meter generation. Data filters were applied to screen unsuitable meters from our analysis, leaving us with 665 meters. The same data are used across all analyses. Ideally, we would have load data from different areas of the country that would reflect local customer usage and weather patterns. However, there are well-known challenges associated with accessing individual customer utility data.

Unfortunately, the data do not represent a true random sample. Our dataset was readily available to the utility because these customers had a long history of interval meter data. Nonetheless, meaningful conclusions can still be drawn from this study due to the size of the sample. More detailed information on the characteristics of the dataset and the filters applied can be found in the SI.

Emissions Data. Marginal emissions factors (MEFs) from Siler-Evans, et al.^{28,29} are used to calculate the net effects of battery behavior on system CO₂, SO₂, and NO_x emissions (see Figure S.7). MEFs capture the emissions rate (kg/MWh) of the marginal generator in a grid region that would be used to respond to changes in load from battery use. Siler-Evans, et al. used hourly emissions and operation data from 1,400 power plants in the U.S. to calculate factors by hour-of-day and season. Estimates of MEF by North American Electric Reliability Corporation (NERC) region are used for each utility tariff in our analysis (California – Western Electricity Coordinating Council (WECC); New York – Northeast Power Coordinating Council (NPCC); Pennsylvania – ReliabilityFirst Corporation (RFC)). The results use MEFs generated from 2014

emissions data. The SI contains an analysis using MEFs generated from average 2006-2014 emissions data which shows slightly higher net emissions. This reflects the ongoing shift from coal to natural gas in the U.S. power mix. We believe this shift will be long-lasting, and therefore chose to use emissions data from 2014.

Tariff and Market Data. C&I customers face two separate charges: one for energy and one for peak demand. Peak demand is typically defined as the highest 15-minutes of power consumption in the billing time period. Some utilities charge different rates based on the time of day, week, or year. We use tariffs from 4 different utilities; Duquesne Light in Pennsylvania, Consolidated Edison (ConEd) in New York, and two California utilities – Pacific Gas & Electric (PG&E) and Southern California Edison (SCE). **Table 2** shows the rate structure used for each utility.

Table 2. Utility Tariffs. Demand and energy charges include the published rate plus all applicable adjustments. Data from OpenEI Utility Rate Database.³⁰

Utility	Demand Charges (\$/kW)	Energy Charges (\$/kWh)
	Summer / Winter	Summer / Winter
ConEd – NY SC-9 – General Large Low Tension Service (NYC)	\$31.66 / 27.06	\$0.035385 / 0.035385
Pacific Gas & Electric (PG&E) – CA E-19 – Medium General Demand TOU (Secondary)	\$15.07 – all periods + \$19.04 / 0.24 – peak + \$4.42 / 0 – mid-peak	\$0.16233 / 0.10185 – peak \$0.10893 / 0.10185 – mid-peak \$0.07397 / 0.07797 – off-peak
Southern California Edison (SCE) – CA General Service – Large; TOU-8, Option B (under 2kV)	\$15.57 – all periods + \$22.95 / 0 – peak + \$6.49 / 0 – mid-peak	\$0.14202 / 0.08899 – peak \$0.08749 / 0.08899 – mid-peak \$0.06288 / 0.0681 – off-peak

Duquesne Light – PA	\$7.09 / 7.09	\$0.090308 / 0.090308
General Service Medium		

While ConEd, PG&E and SCE were chosen because customers can receive incentives for installing batteries, they have very high electricity costs relative to the rest of the country.

Duquesne Light in western Pennsylvania was chosen as a more nationally representative tariff; demand charges are 90% of a rough estimate of the national average and energy charges are 86% of the average. National averages were calculated from the OpenEI Utility Rate Database.

Hourly clearing prices for real-time energy and ancillary services markets were downloaded from grid operators corresponding to the utility tariff being used (California – CAISO; New York – NYISO; Pennsylvania - PJM). Market data for calendar year 2013 are used to match the timing of load data.

Revenue and Emissions Calculations. Outputs from the optimization model include battery charging, discharging and capacity participation in ancillary services for each building at 15-minute intervals. Charging/discharging values are averaged over each hour of the year and matched against the hourly/seasonal MEFs described previously. Battery charging requires increased output, and therefore increased emissions, from the marginal generator, while discharging decreases output from the marginal generator. Net emissions are calculated as the sum of the increased and decreased emissions over the entire year and across all buildings in the dataset. Emissions are normalized to the delivered energy from the battery (e.g., kgCO₂/MWh) for ease of comparison to emissions values from other generation sources and studies.

Total annual revenue from retail and wholesale services is assumed to be constant over the lifetime of the battery (10 years^{31,32}). The present value of the revenue stream from each building is calculated with a discount rate of 15%, and divided by the capital cost to determine the net

present value. A ratio equal to or greater than one indicates a building with favorable economics. We do not include regional subsidies for any scenario. We ignore operational costs in maintaining a battery, assuming that each component (battery cells, inverter, etc.) lasts for the assumed lifetime. The sensitivity of results to lifetime and discount rate are analyzed in the SI.

▪ RESULTS

Storage Economics. Figure 1 shows averaged hourly battery charging/discharging behavior for each utility region under perfect forecasts. Capacity utilization is low because the load peaks that drive battery use are infrequent; the batteries are often idle for days at a time. For the customer-owned and aggregator scenarios, discharging tends to coincide with peak building load because batteries mitigate demand charges. However, charging occurs at different times. Aggregators are exposed to wholesale energy prices, and wait until they reach a minimum overnight before charging the battery. Customer owners face only retail pricing. Under flat-rate energy prices, as with Duquesne Light, customers will recharge as soon as their load profiles decrease in case an unexpected load spike occurs. This coincides with the late afternoon system peak in many U.S. locations. Wholesale-only participation leads to a charging profile similar to the aggregator scenario, but shifts the discharge profile later in the evening when energy prices peak. Tariff design under TOU rates must consider the distribution level impacts of many batteries suddenly charging at the same time when the lowest price block is reached; a similar concept to “smart-charging” schemes proposed for electric vehicle charging.³³

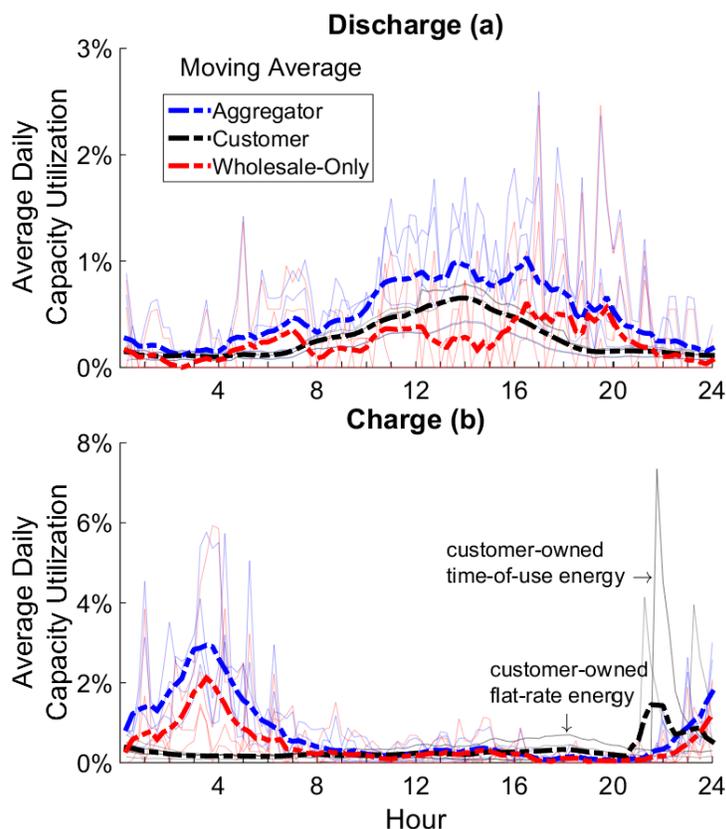


Figure 1. Average daily discharging (a) and charging (b) profile of battery fleet under perfect forecasts (note: different scales). Light solid lines are individual profiles for each ownership perspective and utility region. Heavy dotted lines represent an hourly moving average of all utility regions for a particular ownership perspective. Average capacity utilization is low because the load peaks that drive battery use are infrequent. Customer and aggregator-owned batteries discharge during early afternoon hours when C&I building load peaks, in order to reduce demand charges. Wholesale-only batteries discharge later in the evening when wholesale energy prices peak. Aggregator and wholesale-only batteries charge in the early morning hours when wholesale energy prices are lowest. The charging profile of customer-owned batteries depends on the type of tariff; flat-rate tariffs provide no economic incentive to shift energy, and thus batteries charge as soon as building load begins to decrease in the afternoon while time-of-use tariffs encourage charging as soon as the lowest price block is reached.

Persistence forecasts do a poor job of predicting highly variable market prices and building load, and the batteries fail to meaningfully mitigate demand charges. In reality, forecasting models are more sophisticated but more computationally expensive – a competent trader will fall somewhere in between the perfect and persistence results. The economic results for the persistence forecasts are uninteresting because all buildings are uneconomic, and we therefore choose to discuss only the perfect information cases below. We note that the emissions results from the persistence and perfect forecast cases are very similar.

In the perfect information scenario, a significant number of buildings have favorable economics under ConEd, SCE, and PG&E tariffs *without subsidies*. This is due to high energy costs and demand charges. The economics for Duquesne Light's tariff are mixed. Energy and demand costs are low, which makes peak shaving less profitable, but ancillary service market prices are high in PJM, which helps aggregator-owned batteries. For the base case 60-minute duration battery, annual revenue ranged from \$25-\$112/kWh (installed energy capacity) for customer-owners and \$108-\$181/kWh for aggregators across utility tariffs. The majority of aggregator revenue was generated from demand charge mitigation in all regions except Duquesne Light, where frequency regulation dominated.

Aggregators were able to successfully mitigate demand charges for the customer while simultaneously extracting high value from ancillary service markets. Across all tariffs, the demand charges mitigated under aggregators were nearly identical to those mitigated under the customer-owners for the same size battery, while ancillary service market revenue for aggregators was 89-99% of the revenue in the wholesale-only scenario.

Figure 2 shows battery economics are more favorable at lower durations. While total revenue is higher at longer durations, lower energy capacity utilization means there are decreasing

marginal returns to installing more energy capacity. Moving from a 30-minute to 240-minute duration battery increases capital costs by 300% but revenue by only 57-100% and 64-84% for customer-owners and aggregators, respectively. Demand charge management is typically the largest proportion of revenue, though the revenue share by service can be significantly different across tariffs (Figure S.13).

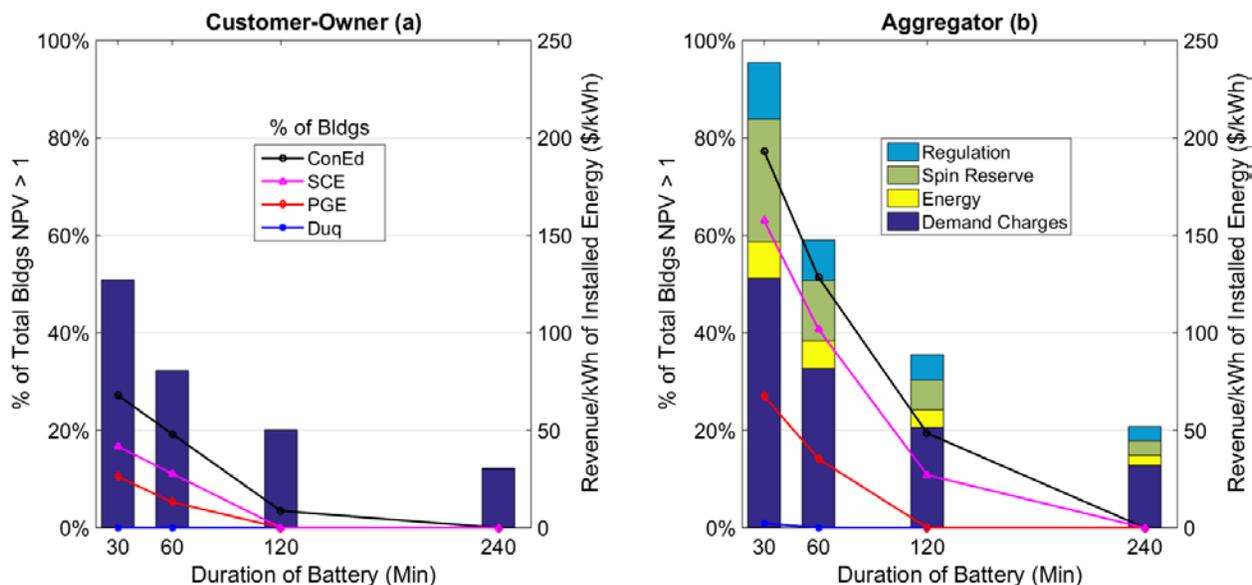


Figure 2. Project economics vs battery duration for customer owners (a) and aggregators (b). Solid lines represent the percent of total buildings that have a net present value greater than 1 in each utility territory. A discount rate of 15% and unsubsidized costs are used in net present value calculations. Bars show the average revenue by service across all tariffs normalized to the installed energy capacity of the battery. Revenue is largely driven by demand charge mitigation where longer duration batteries allow for deeper absolute reductions. However, there are greatly diminishing returns to increases in duration because the extra energy capacity faces a much lower utilization rate. Normalized revenue decreases by nearly 5x as you move from a 30-minute to 240-minute battery. Absolute revenue increases by approximately 75% across the same scale, but cost increases by 300%.

Revenue for batteries in Duquesne Light's territory was driven largely by high prices for ancillary services in PJM, although this was still not enough to make up for low demand charges in creating positive project economics. This region is highly sensitive to installation costs and ancillary service market prices. If system installation costs decrease by 30%, the percent of buildings with positive project economics increases from 0% to 86% for aggregators. However, if ancillary service market prices concurrently decrease by 50%, we again find that no projects have favorable economics (Figure S.16). The sensitivity to ancillary service prices in all regions is noteworthy (Figure S.14).

Battery economics improve significantly for all regions as you decrease installation costs by 30% (~\$750/kWh to ~\$500/kWh). The economics do not change as quickly when varying battery sizing as a percent of the building's peak load or the round-trip efficiency (Figure S.14).

Net Emissions. Figure 3 shows average net emission rates across all storage devices for CO₂, NO_x, and SO₂ for each utility region. Net rates are calculated as increased emissions from charging minus avoided emissions from discharging. Emission rates are relatively insensitive to the chosen battery characteristics (Figure S.10). If the set of buildings is restricted to only those that have favorable economics, the emissions results do not change significantly.

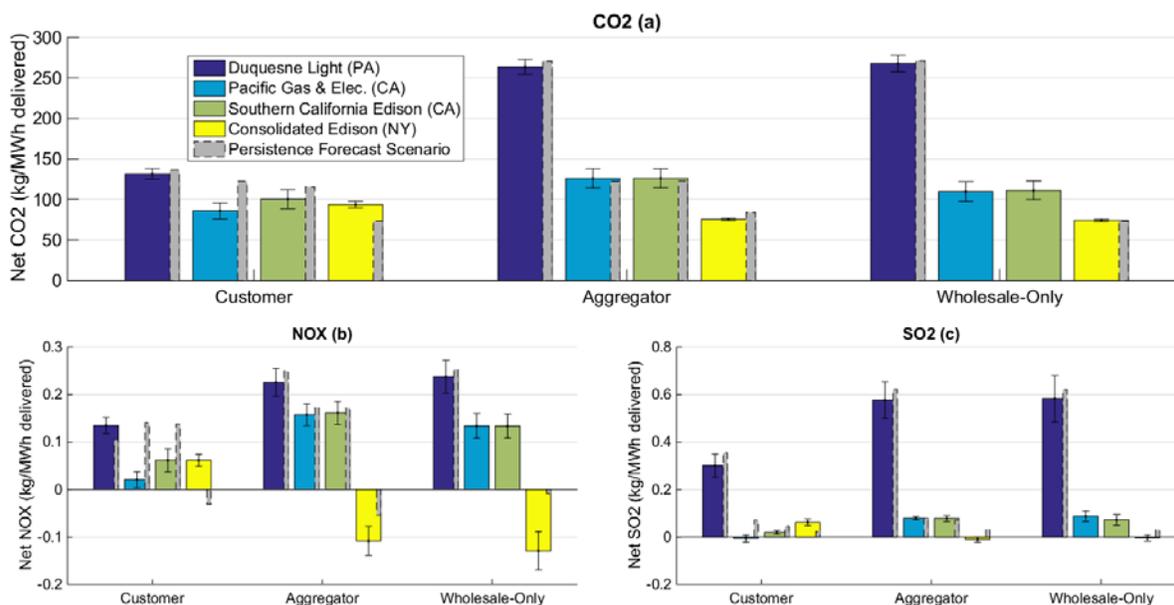


Figure 3. Net CO₂ (a), NO_x (b) and SO₂ (c) emission rates from battery operation across utility tariffs and ownership perspectives. Net rates are calculated as increased emissions from charging minus avoided emissions from discharging. Emission rates are primarily driven by energy losses from inefficiency. Duquesne Light has the highest rates because MEFs are high in RFC and energy losses from frequency regulation are significant. Persistence forecast results are extremely similar to that of perfect forecasts despite their poor accuracy. Persistence forecast emission rates are not shown for the wholesale-only perspective in PG&E and SCE because the values are biased by capacity factors that were essentially zero. In other words, the battery was almost never used and provided very little delivered energy. Net emissions were -370 and -145 kg/MWh in those cases, respectively. Uncertainty bars represent uncertainty in the regression parameter estimates used to calculate marginal emissions factors.

Net CO₂ emission rates with perfect forecasts range from 85 – 130 kg/MWh, 75 – 260 kg/MWh, and 75 – 270 kg/MWh for the customer, aggregator, and wholesale-only perspectives, respectively. Persistence forecast emissions rates are very similar despite low forecast accuracy (gray bars in **Figure 3**). Net NO_x emissions with perfect forecasts range from 0.02 – 0.14

kg/MWh, -0.11 – 0.23 kg/MWh, and -0.13 – 0.24 kg/MWh for the customer, aggregator, and wholesale-only perspectives, respectively. Net SO₂ emissions range from -0.01 – 0.30 kg/MWh, -0.01 – 0.58 kg/MWh, and 0.00 – 0.58 kg/MWh for the customer, aggregator, and wholesale-only perspectives, respectively. Emissions rates are higher for Duquesne Light for two reasons; first, MEFs are higher in RFC and second, battery capacity factors are higher from performing significant amounts of frequency regulation. Higher capacity factors lead to higher round-trip efficiency losses. While Duquesne Light, PG&E, and SCE have higher emission rates in the aggregator and wholesale-only perspectives than the customer perspective, ConEd's emission rates are lower. This is a result of differing marginal emission rates in each region during typical battery charging periods. MEFs in NPCC are lower in the early morning hours when aggregators and other wholesale market participants will charge than in evening hours when customer-owners will charge. RFC and WECC have higher MEFs during early morning hours. This hints at the benefits of a time-of-use (TOU) rate in ConEd that we discuss later.

Positive net emission rates can be attributed to two factors; (1) net positive energy consumption by the battery due to internal battery energy losses, and (2) differences in MEFs between charging and discharging periods. We can isolate the effect of differences in MEFs by calculating the average MEF during battery charge minus the average during discharge, weighted by energy (normalizing the MEF to the energy input/output). The balance of the total emission rate can be attributed to internal energy losses from inefficiency. Across all tariffs, the difference in the average charging-discharging CO₂ MEF is -22, 71, and 25 kg/MWh for customer-owners, aggregators, and wholesale participants, respectively. This represents only -5%, 12%, and 4% of total net emissions rates, respectively. Similar patterns were identified for SO₂ and NO_x. This means that most of the positive net emissions from battery operation can be attributed to internal

energy losses. Figure S.10 confirms that increases in round-trip efficiency dramatically reduce net emission rates.

Tariff design can reduce the environmental impact of BTM batteries, but only with a close examination of a region's generation fuel mix. MEFs reach high and low points at different times during the day depending on your location. MEFs in western states peak in the early morning hours, while at the same time in the northeast they are reaching a minimum. The average daily MEF profile (Figure S.7) shows that TOU rates in California that end in the early evening, and flat rates in Pennsylvania that encourage charging in the late afternoon are optimal for minimizing emissions for customer battery owners. ConEd, however, has a flat-rate tariff which encourages charging during late afternoon hours, while MEFs in NPCC reach a minimum in the early morning hours. We designed a revenue-neutral TOU rate to investigate the impact of tariff design on net emissions. From 8am to midnight, we increase energy rates to 4.27 cents/kWh and decrease rates to 2 cents/kWh from midnight to 8am when MEFs are lowest. Relative to the flat-rate tariff, this lowered net CO₂ emissions by 18% (to 77 kg/MWh), SO₂ by 65% (to 0.02 kg/MWh), and switched batteries from net positive NO_x emissions to net negative (-0.07 kg/MWh). We note that such tariffs must be periodically reexamined as the generation mix and MEFs in a region change.

▪ DISCUSSION

As previous studies have found for grid-scale batteries, BTM batteries increase system emissions in most cases by consuming more energy than they deliver and shifting load between generators. An important finding from our model is that most of the positive net emissions can be attributed to internal energy losses, not to the timing of charging/discharging. Net emission rates from BTM batteries are somewhat lower than rates from natural gas combined-cycle generators, but

have the same order of magnitude. The net emission rates found here are similar in magnitude to those from Hittinger and Azevedo,⁹ who calculated net emission rates across NERC regions from grid-scale batteries performing energy arbitrage only.

Tariff design can reduce the environmental effect of BTM batteries in certain regions, as we have shown with a TOU rate in New York. As the fuel composition of the generation fleet changes in response to regulatory or market forces, policy makers should periodically reassess tariffs for battery owners to encourage charging from low-emission sources. Encouraging aggregators and other wholesale market participants to shift energy purchases to lower emission hours, however, is not as easily accomplished since battery charging follows wholesale market prices. State regulators cannot change wholesale pricing with the stroke of a pen. Instead, this would require broad policy instruments like carbon prices.

The emissions consequences of adding BTM batteries is of significant concern to policy makers where batteries are currently being installed, and they should take care to differentiate between grid-scale and BTM batteries in their analyses. For example, California's Self-Generation Incentive Program (SGIP) mandates that incentivized technologies, such as energy storage, must have a net emission rate lower than that of the grid as a whole. To calculate the emissions for battery storage, they assume all storage devices displace a natural gas combustion turbine by discharging during peak hours and charge during off-peak hours from the output of a combined-cycle gas turbine. Future work to determine a more accurate emissions rate may include production cost modelling.²⁴ These methods apply only to a grid-connected battery by failing to account for retail tariffs and the individual building load profiles which drive BTM battery behavior.

These policy makers are also incentivizing relatively long-duration storage (2-hours for SGIP). Our economic results suggest that greater market penetration may be achieved by allowing shorter duration batteries, which more fully utilize their installed capacity. Regulators can then create a distributed long-duration resource by sequentially calling short-duration assets.

Battery economics improve significantly for all regions as installation costs decrease by 30% (~\$750/kWh to ~\$500/kWh). Tesla forecasts at least a 30% reduction in battery pack cost by the end of the decade,³⁴ which is in-line with academic reviews;³⁵ if the market were to see a corresponding improvement in inverter and soft costs this could significantly increase BTM installations. The degree to which BTM batteries will penetrate locations with average energy costs in this scenario will depend significantly on the price of ancillary services and other location-dependent revenue sources (e.g., demand response programs and/or capacity payments).

Battery owners exposed only to retail tariffs may contribute to, rather than reduce system peak load. The C&I load in our sample peaks earlier than the typical daily system peak, which is consistent with data from national building modeling efforts.³⁶ Under flat-rate retail tariffs, these batteries begin to charge in the early evening as building load drops off. Unfortunately, this increased load coincides with the average system peak and could exacerbate problems and inefficiencies experienced during high load, such as losses and capacity shortfalls.

In some areas of the country, a battery can gain additional revenue from participation in utility demand response (DR) programs or capacity markets. We chose not to include utility DR or capacity market events in our model due to the diversity of program rules in different jurisdictions (e.g., event duration and total number of events) that would make it difficult to compare our model's results across regions. The revenue from participation in such programs could materially improve the economics of BTM batteries. To investigate if the revenue from

DR events would be roughly additive to the revenue in our model, we examined the coincidence of DR events with the provision of other services from the battery. We found that in the case of SCE in summer 2013, the average capacity utilization of the batteries in our model was 4% during the hours of DR events (204 hours). This suggests that the batteries in the model are not typically providing other services during these hours, and that DR revenue should be roughly additive after subtracting increased energy costs from round-trip efficiency losses.

Large-scale mitigation of demand charges will decrease revenue to the utility. This revenue loss will be offset by a decreased need for infrastructure capacity upgrades, but could jeopardize profitability. In this regard we see parallels to the growth of rooftop solar and the associated “value of solar” debate. It will be important for policy makers to consider the lessons learned from the growth of rooftop solar when designing incentives and tariffs for BTM battery owners.

Our findings related to net emission increases hold for the present-day fuel composition of the generation fleet. Should the grid become significantly cleaner, even if it is for only certain portions of the day, then it is possible that the addition of energy storage will decrease overall emissions through load shifting. Lin et al. showed how emissions changes can be related to fuel mix on a small test system.¹³ However, the long lifetime of physical assets for power systems combined with regulatory uncertainty regarding emission reductions from existing generation sources leads us to conclude that significant de-carbonization is many years away, while BTM battery systems are being installed today. Policy makers should be aware of how battery characteristics and tariff design can alter use patterns, and that, short of emissions prices, an adaptive process of tariff redesign may be necessary to link use patterns with emission goals.

ASSOCIATED CONTENT

Supporting Information

Information includes data cleaning and validation, characteristics of the load data, the full optimization formulation and computational methods, an explanation of calculating delivered energy under frequency regulation, and additional results and sensitivity.

AUTHOR INFORMATION

Corresponding Author

* Phone: 914-844-2062; fax: 412-268-3757; e-mail: mjfisher@cmu.edu.

ACKNOWLEDGMENTS

This research was supported by the Carnegie Mellon Electricity Industry Center and used the Extreme Science and Engineering Discovery Environment (XSEDE), which is supported by National Science Foundation grant number ACI-1053575. J.A. received partial support from the Carnegie Mellon Climate and Energy Decision Making Center (CEDM), formed through a cooperative agreement between the National Science Foundation and CMU (SES-0949710). We thank Roberto Gomez for his help in transitioning our code to the Bridges machine at the Pittsburgh Supercomputing Center. We also thank a utility in the Carolinas for providing the load dataset, Inês Azevedo for providing MEFs in digital form, and Jay Whitacre for his suggestions on our battery model.

REFERENCES

(1) Eyer, J.; Corey, G. *Energy Storage for the Electricity Grid: Benefits and Market Potential Assessment Guide*, 2010. Sandia National Laboratories. Albuquerque, NM. <http://www.sandia.gov/ess/publications/SAND2010-0815.pdf>.

(2) *Grid Energy Storage*, 2013. US Department of Energy. Washington, D.C. [http://energy.gov/sites/prod/files/2014/09/f18/Grid Energy Storage December 2013.pdf](http://energy.gov/sites/prod/files/2014/09/f18/Grid_Energy_Storage_December_2013.pdf).

(3) *U.S. Energy Storage Monitor*, 2014. GTM Research & Energy Storage Association. Boston, MA. .

(4) Denholm, P.; Ela, E.; Kirby, B.; Milligan, M. *The Role of Renewable Energy Storage with Renewable Electricity Generation*, 2010. National Renewable Energy Laboratory. Boulder, CO. <http://www.nrel.gov/docs/fy10osti/47187.pdf>.

(5) Decision 14-10-045. *Application of San Diego Gas & Electric Company (U902M) for Approval of its Energy Storage Procurement Framework and Program As Required by Decision 13-10-040*, 2014. California Public Utilities Commission. <http://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M127/K426/127426247.PDF>.

(6) PG&E Self-Generation Incentive Program. <http://www.pge.com/en/mybusiness/save/solar/sgip.page> (accessed Feb 10, 2016).

(7) Consolidated Edison Demand Management Incentives. http://www.coned.com/energyefficiency/demand_management_incentives.asp (accessed Feb 10, 2016).

- (8) 137 FERC 61064. *Frequency Regulation Compensation in the Organized Wholesale Power Markets*, 2011. <https://www.ferc.gov/whats-new/comm-meet/2011/102011/E-28.pdf>.
- (9) Hittinger, E. S.; Azevedo, I. M. L. Bulk energy storage increases United States electricity system emissions. *Environ. Sci. Technol.* **2015**, *49* (5), 3203–3210.
- (10) Hittinger, E.; Whitacre, J. F.; Apt, J. Compensating for wind variability using co-located natural gas generation and energy storage. *Energy Syst.* **2010**, *1* (4), 417–439.
- (11) Denholm, P.; Kulcinski, G. L. Life cycle energy requirements and greenhouse gas emissions from large scale energy storage systems. *Energy Convers. Manag.* **2004**, *45* (13-14), 2153–2172.
- (12) Lueken, R.; Apt, J. The effects of bulk electricity storage on the PJM market. *Energy Syst.* **2014**, *5* (4), 677–704.
- (13) Lin, Y.; Johnson, J. X.; Mathieu, J. L. Emissions impacts of using energy storage for power system reserves. *Appl. Energy* **2016**, *168*, 444–456.
- (14) Carson, R. T.; Novan, K. The private and social economics of bulk electricity storage. *J. Environ. Econ. Manage.* **2013**, *66* (3), 404–423.
- (15) Neubauer, J.; Simpson, M. *Deployment of Behind-The-Meter Energy Storage for Demand Charge Reduction*, 2015. National Renewable Energy Laboratory. Golden, CO. <http://www.nrel.gov/docs/fy15osti/63162.pdf>.
- (16) *Battery Lifetime Analysis and Simulation Tool (BLAST) Documentation*, 2014. National Renewable Energy Laboratory. Golden, CO. <http://www.nrel.gov/docs/fy15osti/63246.pdf>.

- (17) SonnenBatterie Pro. https://sonnen-batterie.com/en-us/sonnenbatterie?_ga=1.42115749.10813948.1465480047#sonnenbatterie-pro (accessed Sep 6, 2016).
- (18) Woody, T. The \$100,000 Battery That Could Help Hotels Save Bundles of Money. <http://www.theatlantic.com/technology/archive/2013/11/the-100-000-battery-that-could-help-hotels-save-bundles-of-money/281194/> (accessed Jun 5, 2016).
- (19) Schoenung, S. *Energy Storage Systems Cost Update*, 2011. Sandia National Laboratories. Albuquerque, NM. <http://prod.sandia.gov/techlib/access-control.cgi/2011/112730.pdf>.
- (20) Tesla Energy: Design Your Powerpack System. <https://www.teslamotors.com/powerpack/design#/> (accessed Feb 6, 2016).
- (21) Ciez, R. E.; Whitacre, J. F. Comparative techno-economic analysis of hybrid micro-grid systems utilizing different battery types. *Energy Convers. Manag.* **2016**, *112*, 435–444.
- (22) de Sisternes, F. J.; Jenkins, J. D.; Botterud, A. The value of energy storage in decarbonizing the electricity sector. *Appl. Energy* **2016**, *175*, 368–379.
- (23) Tesla Motors. Tesla Power System Specifications. <https://www.teslamotors.com/powerpack> (accessed Jun 5, 2016).
- (24) Decision 15-11-027. *Order Instituting Rulemaking Regarding Policies, Procedures and Rules for the California Solar Initiative, the Self-Generation Incentive Program and Other Distributed Generation Issues*, 2015. California Public Utilities Commission. <http://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M156/K044/156044151.PDF>.

(25) Towns, J.; Cockerill, T.; Dahan, M.; Foster, I.; Gaither, K.; Grimshaw, A.; Hazlewood, V.; Lathrop, S.; Lifka, D.; Peterson, G. D.; et al. XSEDE: Accelerating Scientific Discovery. *Comput. Sci. Eng.* **2014**, *16* (5), 62–74.

(26) Eberhard, M. A Bit About Batteries. <https://www.teslamotors.com/blog/bit-about-batteries> (accessed Jan 1, 2016).

(27) 139 FERC 61130. *Order on Compliance Filing*, 2012. Washington, D.C. <https://www.ferc.gov/whats-new/comm-meet/2012/051712/E-4.pdf>.

(28) Siler-Evans, K.; Azevedo, I. L.; Morgan, M. G. Marginal Emissions Factors for the U.S. Electricity System. *Environ. Sci. Technol.* **2012**, *46* (9), 4742–4748.

(29) Siler-Evans, K.; Azevedo, I. L.; Morgan, M. G.; Apt, J. Regional variations in the health, environmental, and climate benefits of wind and solar generation. *Proc. Natl. Acad. Sci.* **2013**, *110* (29), 11768–11773.

(30) OpenEI Utility Rate Database. http://en.openei.org/wiki/Utility_Rate_Database# (accessed Sep 6, 2016).

(31) Kaun, B.; Chen, S. *Cost-Effectiveness of Energy Storage in California: Application of the EPRI Energy Storage Valuation Tool to Inform the California Public Utility Commission Proceeding R. 10-12-007*, 2013. Palo Alto, CA. <http://www.epri.com/abstracts/Pages/ProductAbstract.aspx?ProductId=000000003002001162>.

(32) *2016 Self-Generation Incentive Program Handbook*, 2016. <http://www.cpuc.ca.gov/General.aspx?id=5935>.

(33) Lopes, J. A. P.; Soares, F. J.; Almeida, P. M. R. Integration of Electric Vehicles in the Electric Power System. *Proc. IEEE* **2011**, *99* (1), 168–183.

(34) Motors, T. *Tesla Gigafactory Presentation*, 2015. Palo Alto, CA. https://www.teslamotors.com/sites/default/files/blog_attachments/gigafactory.pdf.

(35) Nykvist, B.; Nilsson, M. Rapidly falling costs of battery packs for electric vehicles. *Nat. Clim. Chang.* **2015**, *5* (4), 329–332.

(36) DOE Office of Energy Efficiency & Renewable Energy. Commercial and Residential Hourly Load Profiles for all TMY3 Locations in the United States. <http://en.openei.org/doi-10.21203/rs.3.rs-1000000/v1> (accessed Jan 1, 2016).

Supporting Information for:

“Emissions and Economics of Behind-the-Meter Electricity Storage”

Michael J. Fisher^{1,} and Jay Apt^{1,2}*

¹ Department of Engineering & Public Policy, Carnegie Mellon University

² Tepper School of Business, Carnegie Mellon University

5000 Forbes Avenue, Pittsburgh, Pennsylvania 15213, United States

Contents

- S1. Data Cleaning and ValidationS-3
- S2. Load and Market DataS-4
- S3. Optimization Formulation and Computational MethodsS-9
 - S3.1 Problem FormulationS-9
 - S3.2 Computational Methods.....S-16
 - S3.3 Software Used.....S-17
- S4. Calculating Delivered Energy While Performing Frequency RegulationS-17
- S5. Additional Results.....S-19
 - S5.1 Emissions – Perfect ForecastS-19
 - S5.2 Economics – Perfect Forecast.....S-25
 - S5.3 Persistence Forecast ResultsS-29
- S6. References.....S-30

* Correspondence to: mjfisher@cmu.edu, 1-914-844-2062

List of Figures

Figure S.1. Distribution of annual average (a) and maximum (b) power consumption across 665 buildings in dataset.	S-4
Figure S.2. Distribution of standard deviation of load across buildings in our sample.	S-5
Figure S.3. Resulting distribution of battery capacity when sized to 20% of peak load.	S-5
Figure S.4. The hour-of-day when the monthly peak building load occurs, given as a distribution across all buildings.	S-6
Figure S.5. Hourly average load across all buildings in the sample vs. outdoor temperature. ...	S-7
Figure S.6. Price-duration curves for real-time energy prices from 2013-2015.	S-8
Figure S.7. 2014 annual average marginal CO ₂ (a), SO ₂ (b), and NO _x (c) emission rates by time-of-day and NERC region. Data from Siler-Evans, et al. ^{11,12} Shaded areas represent one standard error in the regression coefficients used to estimate the emission rates.	S-19
Figure S.8. CO ₂ emission rates using 2014 MEFs vs 2006-2014 average MEFs.	S-20
Figure S.9. NO _x (a) and SO ₂ (b) emission rates using 2014 MEFs vs 2006-2014 average MEFs.	S-21
Figure S.10. Sensitivity of CO ₂ emission rate to battery traits and market conditions.	S-22
Figure S.11. Sensitivity of SO ₂ emission rate to battery traits and market conditions.	S-23
Figure S.12. Sensitivity of NO _x emission rate to battery traits and market conditions.	S-24
Figure S.13. Breakdown of capacity normalized (a) and energy normalized (b) revenue by service for each utility across different battery durations.	S-25
Figure S.14. Sensitivity of economic results to battery characteristics and market conditions.	S-26
Figure S.15. Sensitivity of economic results to financial assumptions.	S-26
Figure S.16. Sensitivity of economic results to ancillary service prices when battery cost declines to \$400/kWh + \$267/kW (~\$500/kWh).	S-27
Figure S.17. Effect of sales tax on project economics.	S-27
Figure S.18. Demand charge reduction under aggregator ownership across different battery durations.	S-28
Figure S.19. Average daily discharging (a) and charging (b) profile of battery fleet under perfect forecasts.	S-29
Figure S.20. Sensitivity of economic results to system cost under persistence forecasts.	S-30

List of Tables

Table S.1. Grid Node Locations for Market Data	S-7
---	-----

S1. Data Cleaning and Validation

The utility provided data from a subset of their entire commercial and industrial population. The subset were those customers who had interval meters and a sufficiently long history for this study. This may introduce selection bias. The subset of customers with interval meters would suggest a skew toward higher usage customers relative to the general commercial/industrial population. Our results could also be biased because the data come from one geographic area of the country. Commercial/industrial customers in other parts of the country could have different load shapes that would affect battery behavior.

Meters covering loads unsuitable for this study were removed according to usage characteristics. This included any meters with maximum power draw less than 25kW, average power draw less than 13kW, or any meter missing a total of more than 2 days of data within 2013. Data gaps for meters with less than 2 days of missing data were filled with an average profile from two surrounding days of the same type (weekday/weekend). 270 meters were removed during this step. A subsequent visual inspection of each meter's load profile identified meters that were attached to specific pieces of equipment (e.g., switching between 2 discrete load values throughout the year). 59 meters were removed during this step.

It is very difficult to validate the results of our model by comparing to real-world battery behavior. BTM batteries are currently installed at a small fraction of customer sites even in California. Metered output data from these batteries is confidential to the customer, and proprietary to the third-party aggregators who may have installed the battery. There is some capacity factor data from PG&E impact evaluation reports for the Self-Generation Incentive Program (SGIP),¹ though it is quite coarse and calculated from only 4 projects. The impact report states 80% of monthly capacity factors for installed batteries were below 10%, with nearly

60% below 2.5%. For the batteries modeled in this study under a PG&E tariff, 100% of monthly capacity factors were below 10%, and 95% below 2.5%. For SCE's tariff, 100% of monthly capacity factors were below 10%, and 76% below 2.5%. The lower capacity factors found in this study could be the result of our decision not to model demand response (DR) events or behind-the-meter (BTM) solar photovoltaic generation. DR event participation is a requirement of receiving an incentive under SGIP.

S2. Load and Market Data

Our dataset included energy usage (kWh) data from 994 individual commercial and industrial meters at a 15-minute sample rate for 1 calendar year (2013). According to the utility, none of the customers had behind-the-meter generation. As described in the previous section, data filters were applied to screen unsuitable meters from our analysis, leaving us with 665 meters.

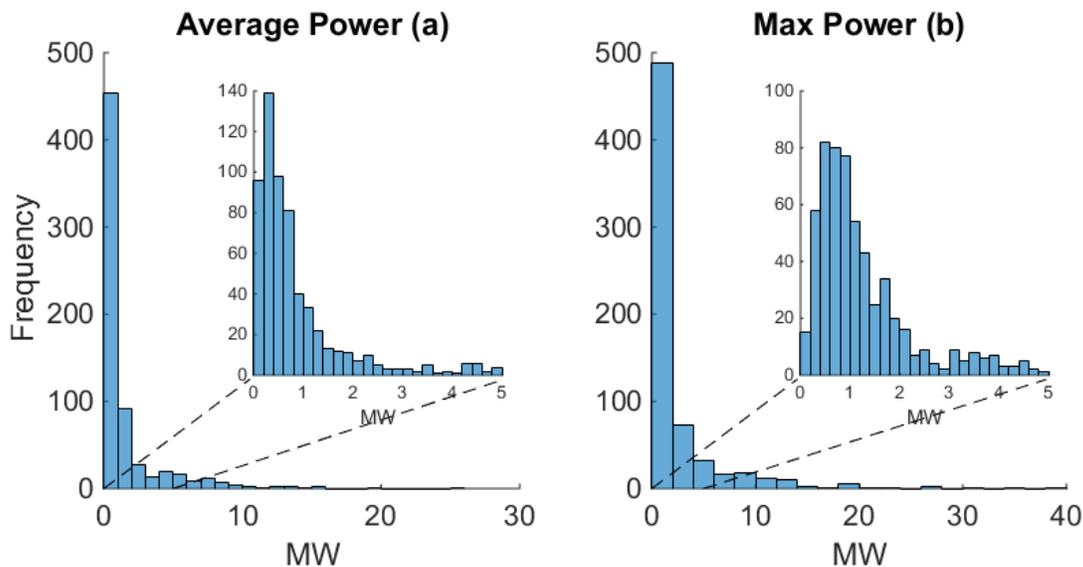


Figure S.1. Distribution of annual average (a) and maximum (b) power consumption across 665 buildings in dataset.

Figure S.1 shows the distribution of annual average and maximum power consumption for the 665 buildings in the sample. The median annual average power consumption is 600 kW, and the median peak power consumption is 1,094 kW. These distributions expose a long tail in power consumption. Removing all buildings with maximum annual power consumption greater than 10 MW (37 buildings) changes the emission rates for all pollutants by less than 2% when compared with the results of the full sample.

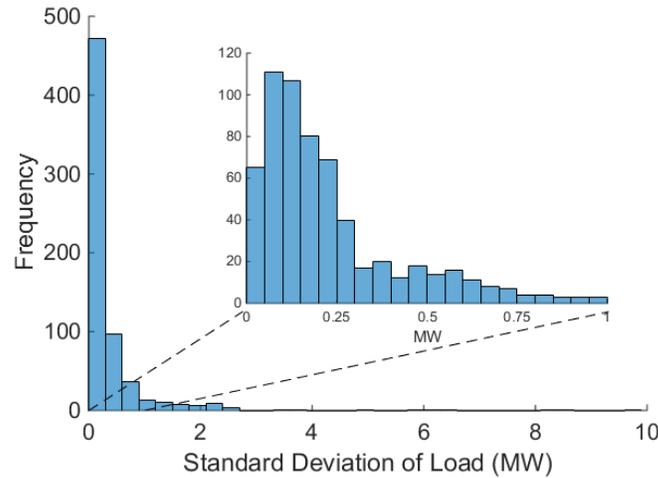


Figure S.2. Distribution of standard deviation of load across buildings in our sample.

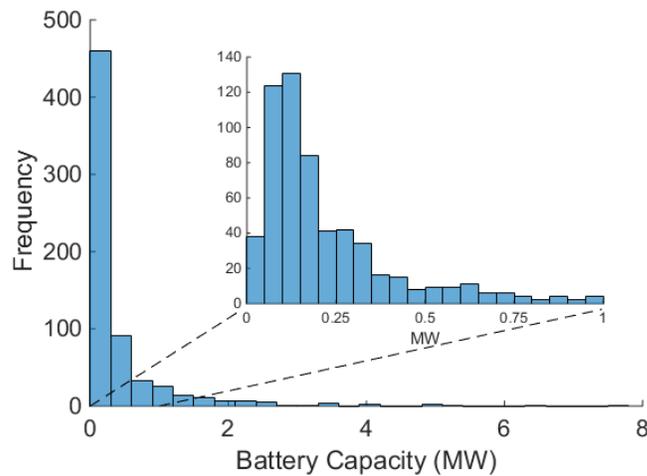


Figure S.3. Resulting distribution of battery capacity when sized to 20% of peak load.

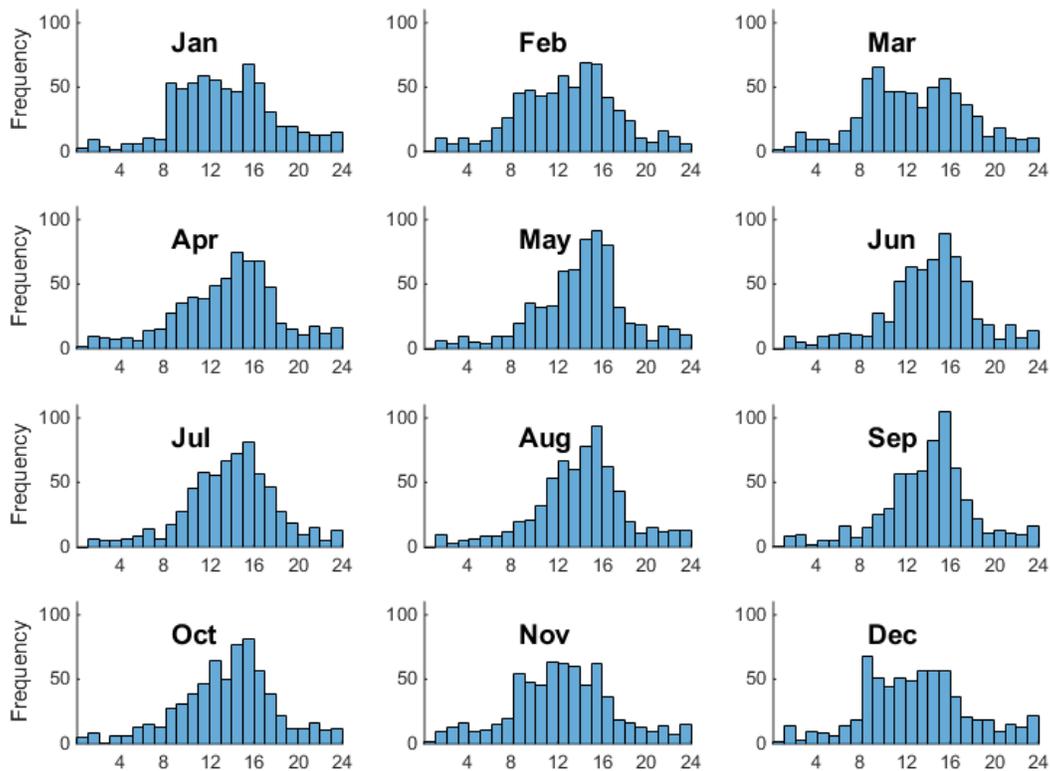


Figure S.4. The hour-of-day when the monthly peak building load occurs, given as a distribution across all buildings. Monthly peaks tend to concentrate in the early afternoon hours during the summer, while in the winter they spread out over a wider portion of the day. This is likely due to the effect of air conditioning load driven by the southern climate where the data originate.

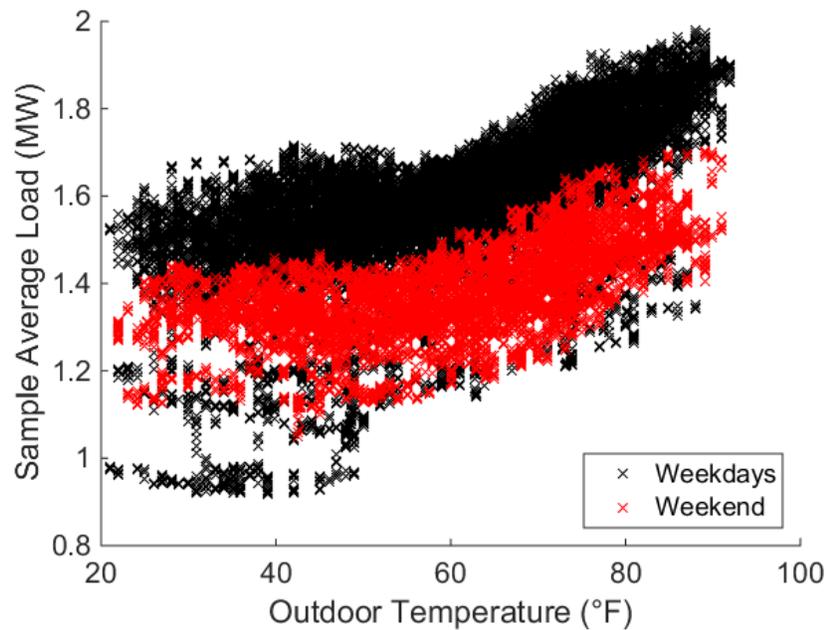


Figure S.5. Hourly average load across all buildings in the sample vs. outdoor temperature. Air conditioning load is likely responsible for the temperature dependence of load above approximately 60 degrees Fahrenheit.

Calendar year 2013 hourly clearing prices for real-time energy and ancillary services markets were downloaded from grid operators in the United States corresponding to the utility tariff being used (California – CAISO; New York – NYISO; Pennsylvania - PJM). Table S.1 shows the grid node location where data were selected. Some California ancillary services only have a day-ahead market.

Table S.1. Grid Node Locations for Market Data

Grid Region	Node ID
PJM (Duquesne Light)	Western Hub (51288)
NYISO (ConEd)	N.Y.C. (61761)
CAISO (PGE)	TH_NP15_GEN_APND
CAISO (SCE)	TH_SP15_GEN_APND

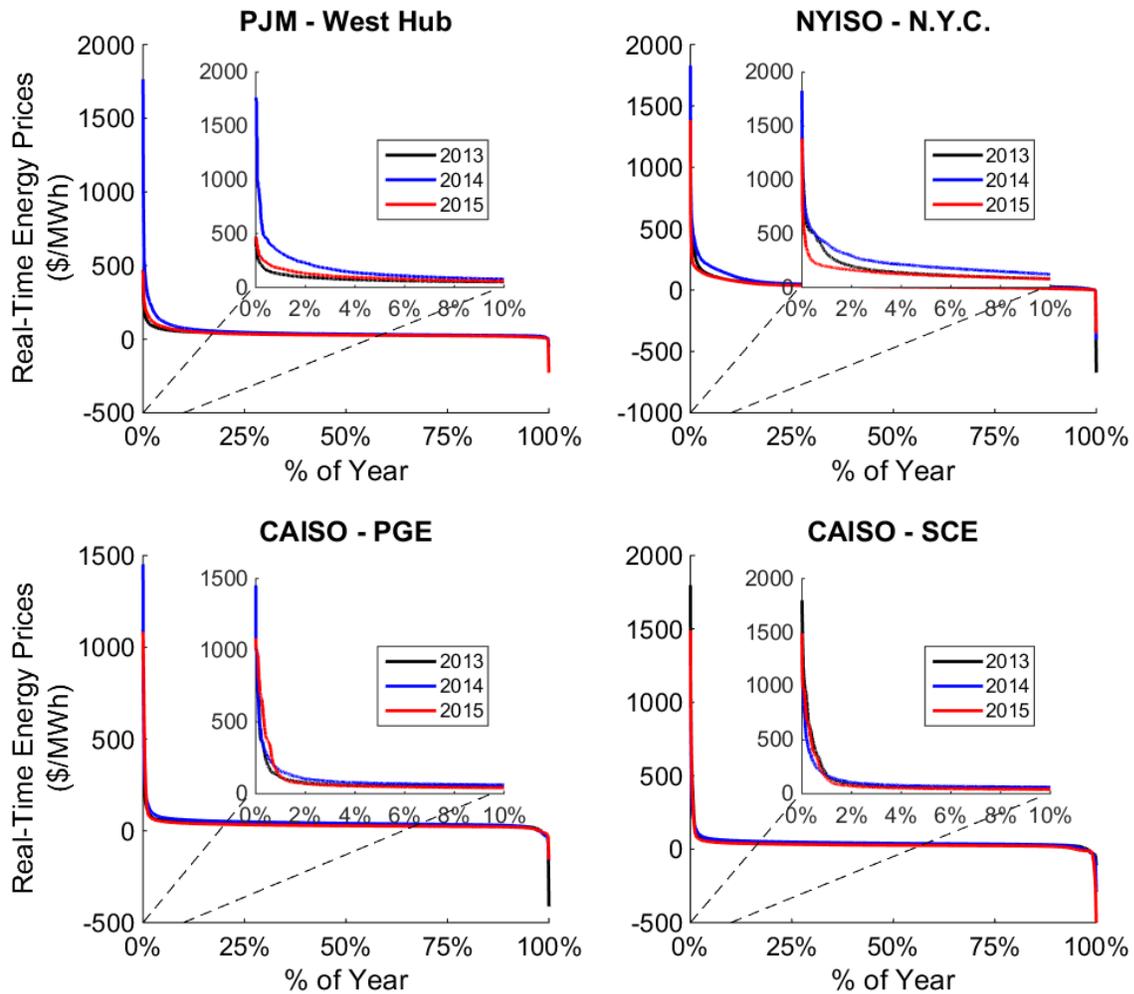


Figure S.6. Price-duration curves for real-time energy prices from 2013-2015. Ancillary service prices show similar trends because the largest component of ancillary service prices is typically the lost opportunity cost of producing energy (valued at the real-time price).

Figure S.6 shows that 2013 market prices are not significantly different from 2015 prices, with 2014 prices in NYISO and PJM affected by extreme cold temperatures (“polar vortex” event). It

would be inappropriate to compare 2013 data to earlier periods due to changes in market structure, such as the implementation of FERC Order 755.²

S3. Optimization Formulation and Computational Methods

S3.1 Problem Formulation

Constants

\overline{SoC}	Max state of charge of battery (kWh)
SoC(0)	Initial state of charge of battery (kWh)
\bar{P}	Rated power of battery (kW)
η	round-trip efficiency of battery (%)
BL(t)	building load at time t (kW)
EC(t)	Energy cost at time t (\$/kWh)
DC _k	Demand charge for demand period k (\$/kW)
BRC	Battery Replacement Cost (\$)
LMP(t)	Wholesale energy cost at time t (\$/kWh)
REGP(t)	Wholesale regulation market price at time t (\$/kWh)
SPINP(t)	Wholesale spinning reserve market price at time t (\$/kWh)
RDNE	Regulation Down Net Energy (kWh/kW) – maximum amount of net energy charge during a typical hour of frequency regulation. Expressed as a fraction of the regulation capacity offered.
RUNE	Regulation Up Net Energy (kWh/kW) – maximum amount of net energy discharge during a typical hour of frequency regulation. Expressed as a fraction of the regulation capacity offered.

ABSE Absolute Energy (kWh/kW) – total energy processed by a battery during frequency regulation. Expressed as a fraction of the regulation capacity offered.

Variables

c(t) battery charging at time t (kW)
d(t) battery discharge at time t (kW)
reg(t) frequency regulation capacity participation at time t (kW)
spin(t) spinning reserve participation at time t (kW)
pd_k peak demand during demand period k (kW)
soc(t) state of charge of battery at time t (kWh)
nl(t) net load at time t (kW)
deg(t) battery degradation cost at time t (\$)
pen(t) penalty function to prefer 90% idle state of charge (\$)

Sets

T Set of 15-minute time periods
K Set of demand periods (e.g. peak, mid-peak and off-peak - depends on tariff), each of which is a subset of T

Objective Functions

$$\min \sum_{t \in T} [EC(t) * nl(t) + deg(t) + pen(t)]/4 + \sum_{k \in K} DC_k * pd_k \tag{1}$$

$$\min \sum_{t \in T} [(LMP(t) + EC(t)) * nl(t) - REGP(t) * reg(t) - SPINP(t) * spin(t)]/4 + deg(t) + pen(t) + \sum_{k \in K} DC_k * pd_k \tag{2}$$

$$\min \sum_{t \in T} [LMP(t) * nl(t) - REGP(t) * reg(t) - SPINP(t) * spin(t)]/4 + deg(t) + pen(t) \quad (3)$$

Equation 1 is the objective function for the customer ownership perspective. Equation 2 is for aggregators and equation 2 is for the wholesale-only perspective. We divide the energy cost and ancillary service revenue by 4 to convert kW to kWh for a 15-minute time-step. This correctly matches the units of market clearing prices (\$/kWh). This portion of the objective function represent real costs/revenues to the battery owner. Degradation is an amortization of the assumed replacement cost into the use phase of the battery; it prevents the unnecessary use of the battery to perform services when market prices are low. The penalty function is used to restrict battery SOC as discussed below.

The last term in the customer and aggregator objective functions sums demand charges over each demand period k ; the form of this portion of the equation will change depending on the structure of demand charges in each utility tariffs. For example, Duquesne Light's demand charge is a flat-rate charge covering all hours of a month and does not depend on time-of-day or month – therefore there is only one demand period k . Southern California Edison (SCE), on the other hand, has a more nuanced demand charge that has a flat-rate charge for all hours of a month, as well as time-of-day adders that depend on the month. In this case, there are 4 different demand periods to track in any given month. The code implementation of tracking peak demand in each demand period in the GAMS software, while maintaining a linear programming problem, warrants some discussion. The use of a maximum function (MAX) common to many software packages is not a linear function, and therefore would necessitate the use of a non-linear solver in the optimization calculations. This would drastically slow the solution time. Fortunately, there is an equivalent method to a MAX function that maintains a linear programming problem. We

create a number of extra variables equal to the number of demand periods we need to track (for SCE, this was 4). The variables will track the peak demand in each of these periods. We then add an equivalent number of constraints at each time step to our problem (again, 4 for SCE at each time step) that force the variable to assume the maximum load experienced during that period. These take the form $nl(t) \leq pd_k \quad \forall t \in k$ where $nl(t)$ is the net load at time t where t falls in demand period k and pd_k is the variable that holds the max load for demand period k . A similar method is used in the imperfect information scenarios to provide “memory” of the previous demand peak across each rolling-horizon optimization in a given month.

Where:

$$nl(t) = BL(t) + c(t) - d(t) \quad (4)$$

$$deg(t) = \frac{\sqrt{\eta} * c(t) + \frac{d(t)}{\sqrt{\eta}} + reg(t) * ABSE}{4 * SoC * 4598} * BRC \quad (5)$$

Equation 4 calculates the net load of the building at time t (the load seen by the meter) from the underlying building load and the charging or discharging of the battery.

Equation 5 calculates degradation cost at time t as the product of the replacement capital cost and the fraction of total lifetime energy processed by the battery at time t . As determined by experimental results in Peterson, et al.,³ we account only for amp-hours processed by the battery, not depth of discharge, when calculating battery degradation for lithium-ion phosphate batteries. Based on data in Peterson, et al., we assume that the energy consumed to reach the end of battery lifetime (80% of initial battery capacity) is 4,598 times the maximum SOC. We derive this number from an average of the model coefficients reported in the paper. To express the energy processed by the battery at time t in fractions of lifetime energy, we divide the energy processed

(sum of charging, discharging, and regulation energy) by the lifetime energy capacity of the battery (4,598 times maximum SOC). We divide by 4 to convert charge, discharge, and regulation kW to kWh. Battery replacement cost is assumed to be 70% of the current system cost. Battery behavior is relatively insensitive to the replacement cost assumption.

Absolute Energy (ABSE), used in Equation 5, is the total amount of energy processed by the battery during participation in frequency regulation, both by charging and discharging, expressed as a fraction of the regulation capacity offer (kWh/kW). We derive the value for ABSE (0.26 kWh/kW) from 1 year of PJM regulation D signal⁴ (2 second sample rate). This parameter is calculated as the mean value in the distribution of absolute energy processed by the battery in one hour of frequency regulation.

$$pen(t) \geq (\overline{SoC} * 0.9 - soc(t)) * 10^{-7} \quad (6)$$

$$pen(t) \geq (soc(t) - \overline{SoC} * 0.9) * 10^{-1} \quad (7)$$

Equations 6 and 7 implement a penalty function for deviations from 90% state of charge. This forces the battery to prefer a 90% SOC when idle, balancing a desire for higher states of charge to be ready for unexpected spikes in energy use while recognizing that operation above 90% SOC may be harmful to the battery (due to high voltage).⁵ Different scaling factors are used to accomplish different objectives. A small scaling factor of 10E-7 is used in Equation 6, which creates a penalty for SOC lower than 90%, to reflect the preference for higher SOC, but not at the expense of revenue generating activities that require discharging. A larger scaling factor of 10E-1 is used for Equation 7, which creates a penalty for SOC higher than 90%, to reflect higher degradation rates at high voltages. The combination of these two formulas are mathematically

equivalent to an absolute value calculation, but this formulation preserves the overall problem as a linear program and allows different penalties for SOC above and below 90%.

The problem is initialized with a 90% SOC at $t = 0$.

Constraints

$$soc(t + 1) = soc(t) + \frac{\sqrt{\eta} * c(t) - \frac{d(t)}{\sqrt{\eta}} - reg(t) * ABSE * (1 - \eta)}{4} \quad (8)$$

Equation 8 is an intertemporal constraint to track changes in SOC. We divide by 4 to convert charge, discharge, and regulation kW to kWh. Charging/discharging results in internal energy loss, which is characterized by the round-trip efficiency (η). While net energy neutral, frequency regulation causes charging/discharging and therefore losses. As described previously, ABSE is used to calculate the amount of energy processed while providing frequency regulation. As a simplification, we assume that the battery is never called to provide spinning reserve, and thus does not suffer any energy losses for this service. We ignore standby losses as they are small (~1-2% per month),⁶ which causes us to slightly underestimate emissions rates and slightly overestimate revenues to the owner.

$$0 \leq c(t) \leq \bar{P} \quad (9)$$

$$0 \leq d(t) \leq \bar{P} \quad (10)$$

Equations 9 and 10 restrict the charging and discharging power to the rated power of the battery.

$$0.2 \leq soc(t) \leq \overline{SoC} \quad (11)$$

The state of charge (SOC), expressed as a fraction of total charge carrying capacity, is restricted to values between 20% and 100% in Equation 11. The lower limit of 20% is imposed

to prevent degradation at low voltages. Lithium-ion batteries in electric vehicles have similar constraints imposed by car manufacturers.⁷

$$reg(t) \leq \bar{P} - c(t) - d(t) - spin(t) \quad (12)$$

Equation 12 limits the amount of regulation capacity the battery can offer to the rated power of the battery minus any net charging or discharging of the battery and the capacity held for spinning reserve. In the customer ownership case where participation in ancillary service markets is not allowed, this equation is still valid and simply limits the charging and discharging of the battery. We assume that the regulation signal is designed to be energy neutral, as with PJM's dynamic signal for fast-responding resources.⁸

$$\overline{SoC} \geq soc(t) + RDNE * reg(t) \quad (13)$$

$$\overline{SoC} \leq 5 * (soc(t) - RUNE * reg(t)) \quad (14)$$

Equations 13 and 14 constrain the amount of regulation capacity the battery can offer based on the state of the charge of the battery. Equation 13 prevents the SOC from exceeding the maximum SOC while Equation 14 ensures a minimum 20% SOC. The frequency regulation signal will cause the battery to temporarily charge and/or discharge. We do not want the battery to violate the state of charge constraints at any time during regulation participation so we must adjust the regulation capacity offer to account for the maximum amount of net energy charge/discharge typically experienced while providing frequency regulation. We derive the values for RDNE (0.1 kWh/kW) and RUNE (0.2 kWh/kW) from 1 year of PJM regulation D signal⁴ and express the value as a fraction of the regulation capacity offer. These parameters are set at the 97.5% percentile of the distribution of net energy charge/discharge during each hour of regulation signal, as opposed to the 100% percentile, to not overly constrict frequency regulation participation due to a few hours of atypical regulation signal patterns. The resulting values for

RDNE and RENE are very similar to the values of corresponding parameters used in EPRI's battery storage modelling for California (0.13 and 0.11, respectively).⁹

S3.2 Computational Methods

We have six optimization runs to perform for every choice of tariff scheme or battery configuration – three ownership perspectives mixed with two forecasting scenarios. In the perfect information scenarios, we feed an entire calendar month of data to the optimization model to minimize energy costs for that billing period. Some information, such as the battery state of charge and building net load are stored to initialize the next month's optimization run. We conduct 12 separate monthly optimizations for each building, totaling approximately 8,000 optimizations across all buildings. With a 12-core Intel Xeon E5-2680 v3 CPU at 2.5GHz and 64GB of memory this took approximately 10 minutes.

In reality, battery operation software would need to make operational decisions about the current time period using imperfect forecasts and update those forecasts as time progressed. Our persistence forecast scenarios therefore require much more computational effort. We conduct a rolling horizon optimization for each 15-minute window in which we save only the operational decision about the current period. We then step forward 15 minutes, make a new forecast, and re-optimize over the selected time horizon. We selected a horizon of 14 hours based on a set of trials to determine the best performance across horizon lengths. In this way, we conduct approximately 35,000 optimizations (1 year of 15-minute periods) for each building, totaling 23 million separate optimizations across all buildings. These optimizations were performed on the Bridges Supercomputer at the Pittsburgh Supercomputing Center through an allocation by the National Science Foundation's Extreme Science and Engineering Discovery Environment (XSEDE) Program.¹⁰ A single computing node with two 14-core Intel Xeon E5-2695 v3 CPU at

2.3GHz and 128GB of memory took approximately 3 hours to run all buildings for a single set of parameters. Sensitivity analysis was performed by feeding multiple parameter scenarios to different computing nodes at the same time.

S3.3 Software Used

The battery configuration, data and optimization parameters are initially set in MATLAB. MATLAB selects the appropriate window of data for each building and performs the persistence forecasts. These data are written to a .GDX file that can be read by the optimization software. MATLAB creates a set of parallel workers on all but one available core (to allow for a “scheduling” core) and the parallel code is executed via a parallel loop. When the optimization software finishes its routine, the results are again written to a .GDX file which MATLAB can read and store. The battery optimization is performed in the General Algebraic Modeling System (GAMS) using the CPLEX solver.

S4. Calculating Delivered Energy While Performing Frequency Regulation

Emissions results presented in this paper are normalized to the amount of energy delivered by the battery for ease of comparison to emissions values from other generation sources and emissions studies. The amount of energy delivered while performing frequency regulation is not a straightforward calculation – it depends on what other services the battery is providing at the same time.

1. Frequency Regulation Only – if the battery is only performing frequency regulation, we estimate the delivered energy by multiplying the capacity offered for frequency regulation by half the value of the ABSE metric discussed in section S3.1 (“Absolute

Energy” processed during frequency regulation). Since we assume the frequency regulation signal is energy neutral over a given timeframe, the amount of energy delivered during that timeframe must be half the total energy processed.

2. Frequency Regulation while Charging – if the battery is charging and providing frequency regulation, we estimate that it will deliver *zero* energy if the charge energy is higher than half the ABSE times the regulation capacity offered. In other words, if the battery is charging at a sufficiently fast rate we assume that dips in the frequency regulation signal will not cause the battery to discharge at any point while providing this service. If the charge energy is lower than half the ABSE times the regulation capacity offered, we subtract the former from the latter to calculate the delivered energy.
3. Frequency Regulation while Discharging – similarly, if the battery is discharging and providing frequency regulation, we make no adjustments to the delivered energy from discharging as long as the discharge energy is more than half the ABSE times the regulation capacity offered. If not, we adjust the delivered energy from discharging by half the ABSE times the regulation capacity offered.

S5. Additional Results

S5.1 Emissions – Perfect Forecast

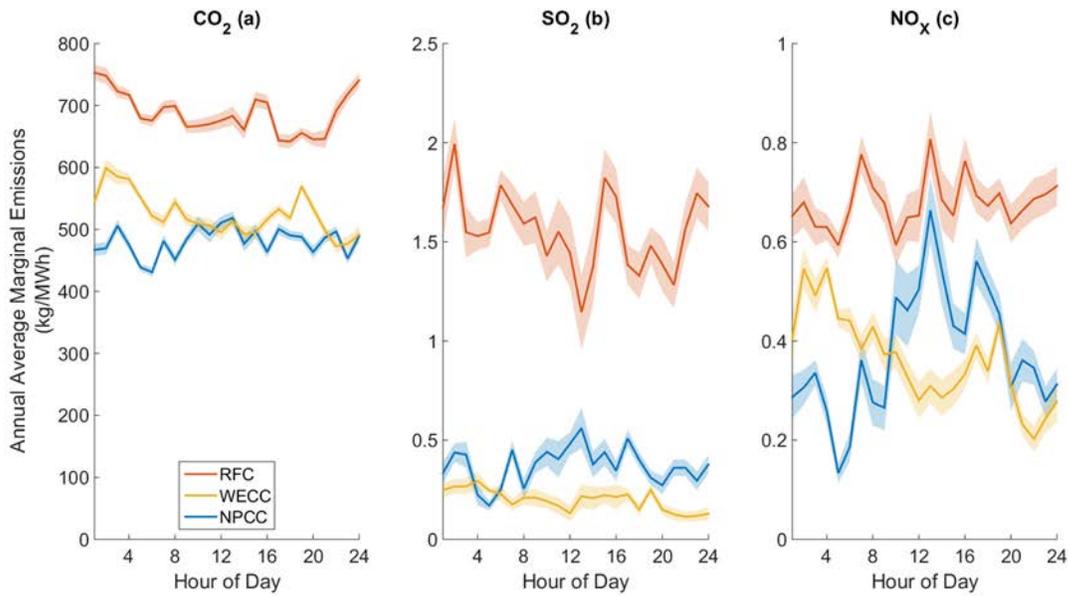


Figure S.7. 2014 annual average marginal CO₂ (a), SO₂ (b), and NO_x (c) emission rates by time-of-day and NERC region. Data from Siler-Evans, et al.^{11,12} Shaded areas represent one standard error in the regression coefficients used to estimate the emission rates.

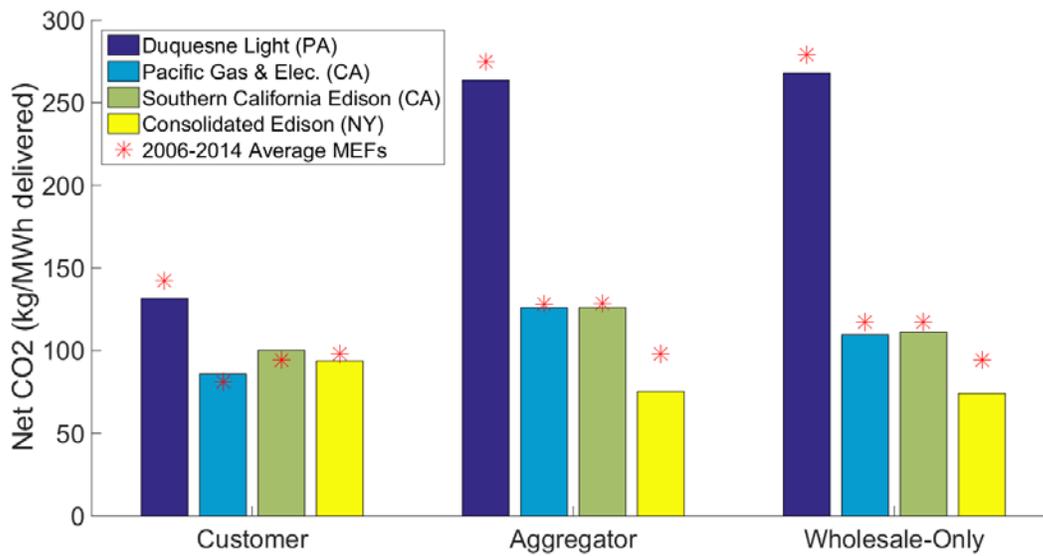


Figure S.8. CO₂ emission rates using 2014 MEFs vs 2006-2014 average MEFs. Colored bars show results using 2014 MEFs, which were presented in the main article (Figure 3). Red asterisks show results using 2006-2014 average MEFs.

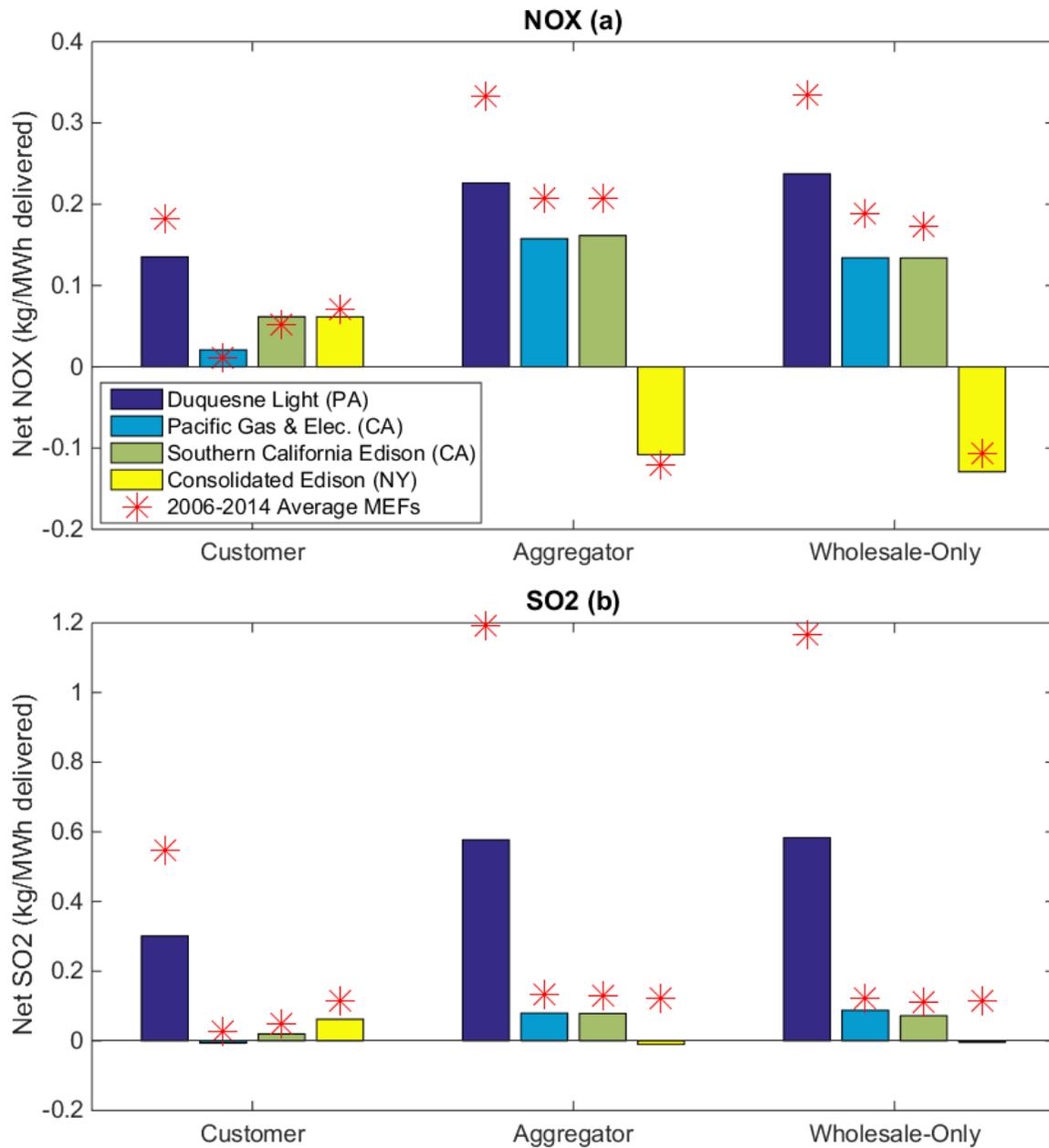


Figure S.9. NO_x (a) and SO₂ (b) emission rates using 2014 MEFs vs 2006-2014 average MEFs.

Colored bars show results using 2014 MEFs, which were presented in the main article. Red asterisks show results using 2006-2014 average MEFs.

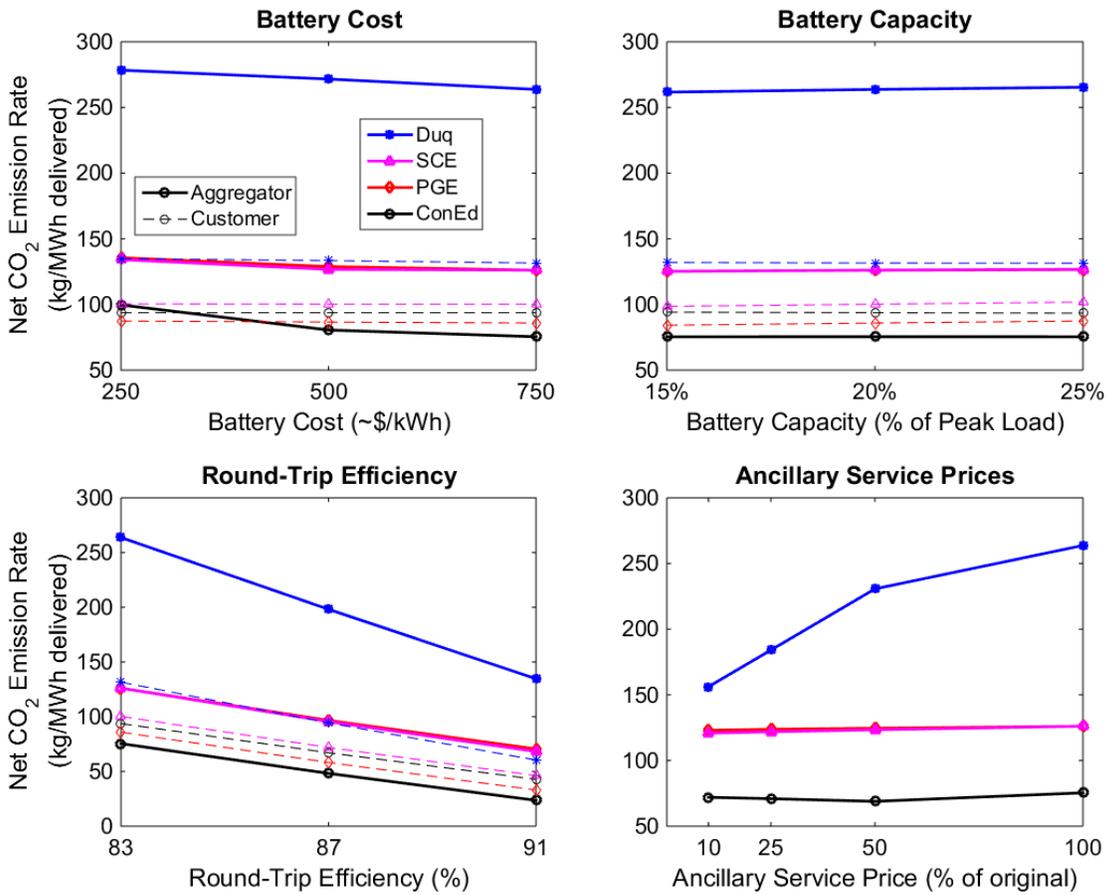


Figure S.10. Sensitivity of CO₂ emission rate to battery traits and market conditions. In our model, lower capital costs lead to higher capacity factors and thus larger emission rates. Lower battery cost can actually boost revenue by decreasing perceived degradation costs. A drop in degradation costs depresses the threshold for profitable participation in peak shaving or ancillary services, allowing the battery to generate more revenue through higher utilization.

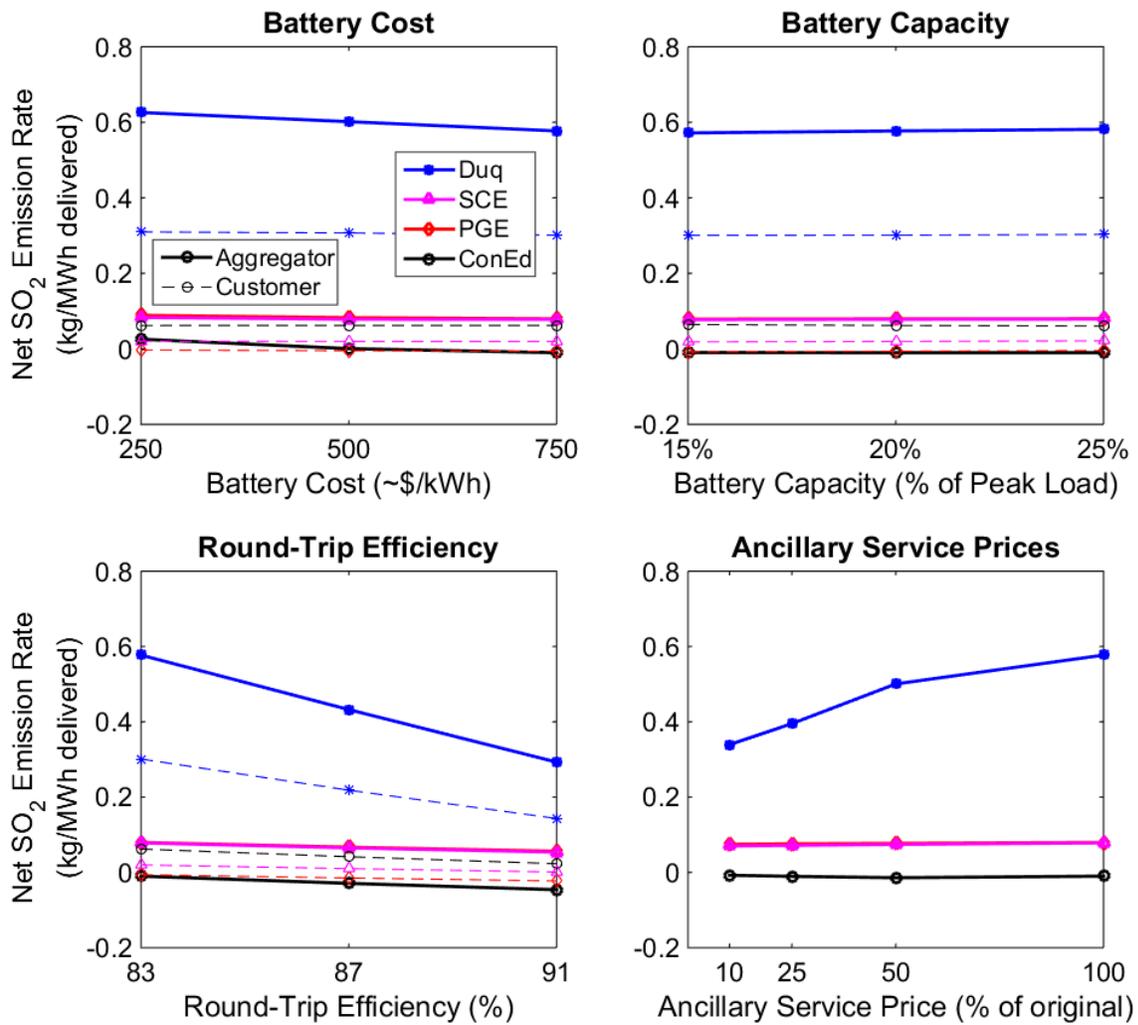


Figure S.11. Sensitivity of SO₂ emission rate to battery traits and market conditions.

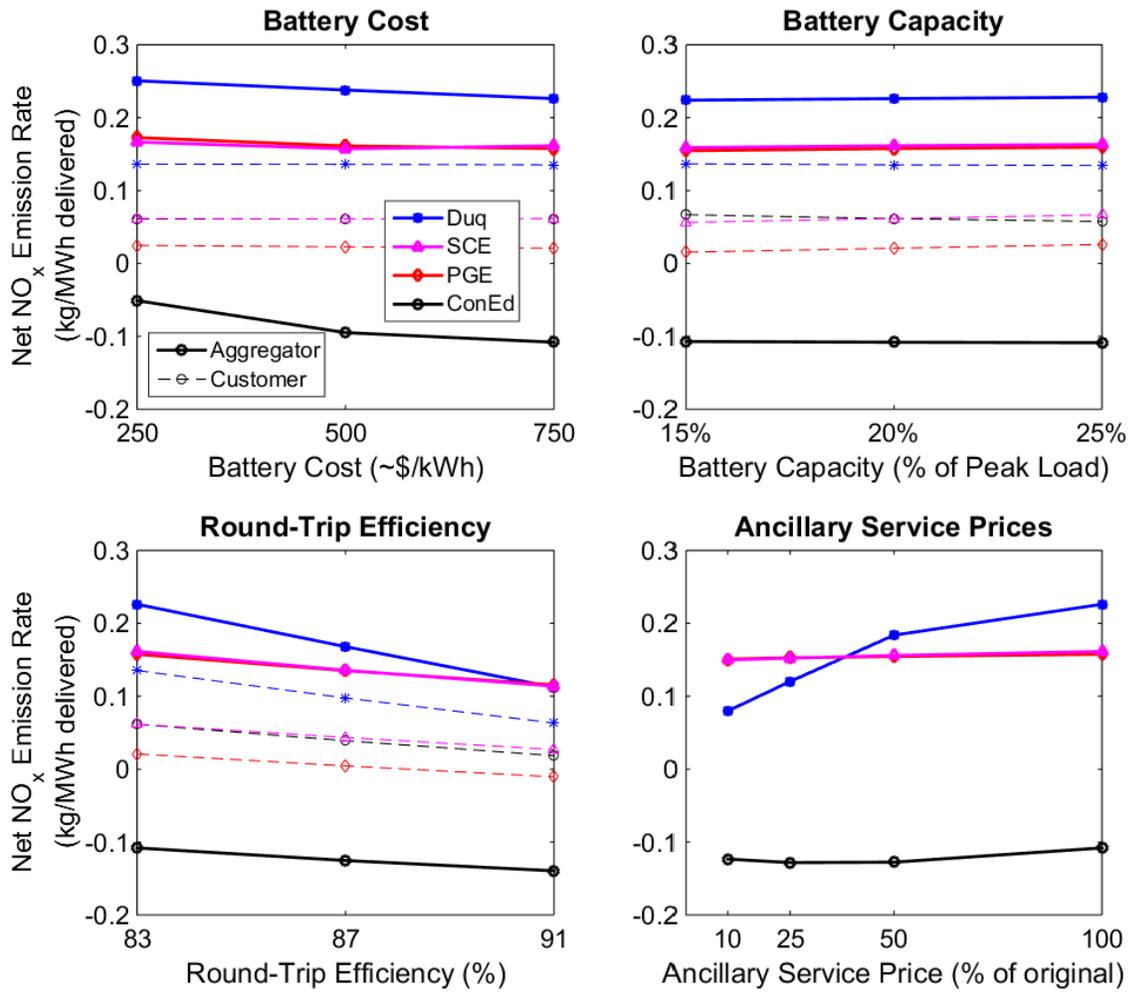


Figure S.12. Sensitivity of NO_x emission rate to battery traits and market conditions.

S5.2 Economics – Perfect Forecast

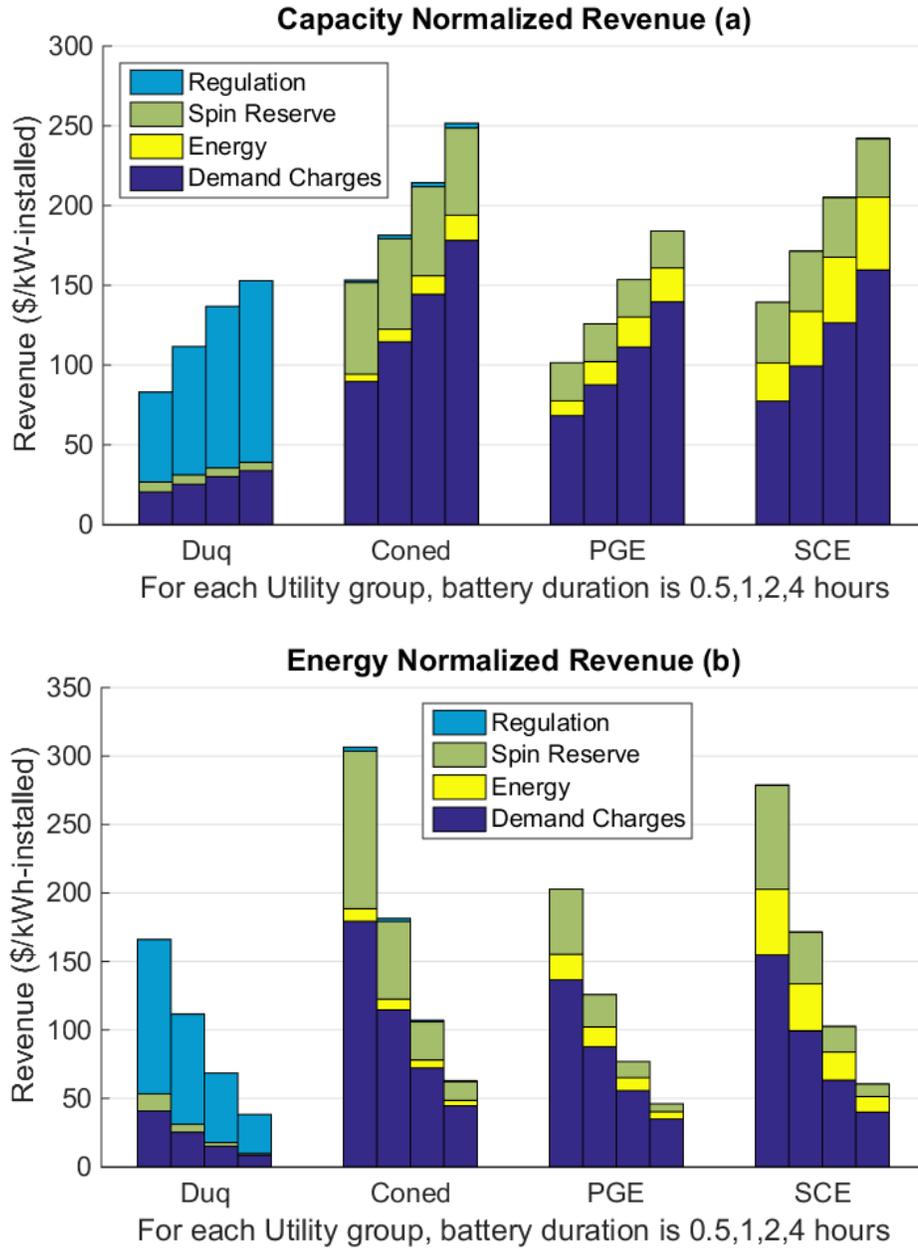


Figure S.13. Breakdown of capacity normalized (a) and energy normalized (b) revenue by service for each utility across different battery durations.

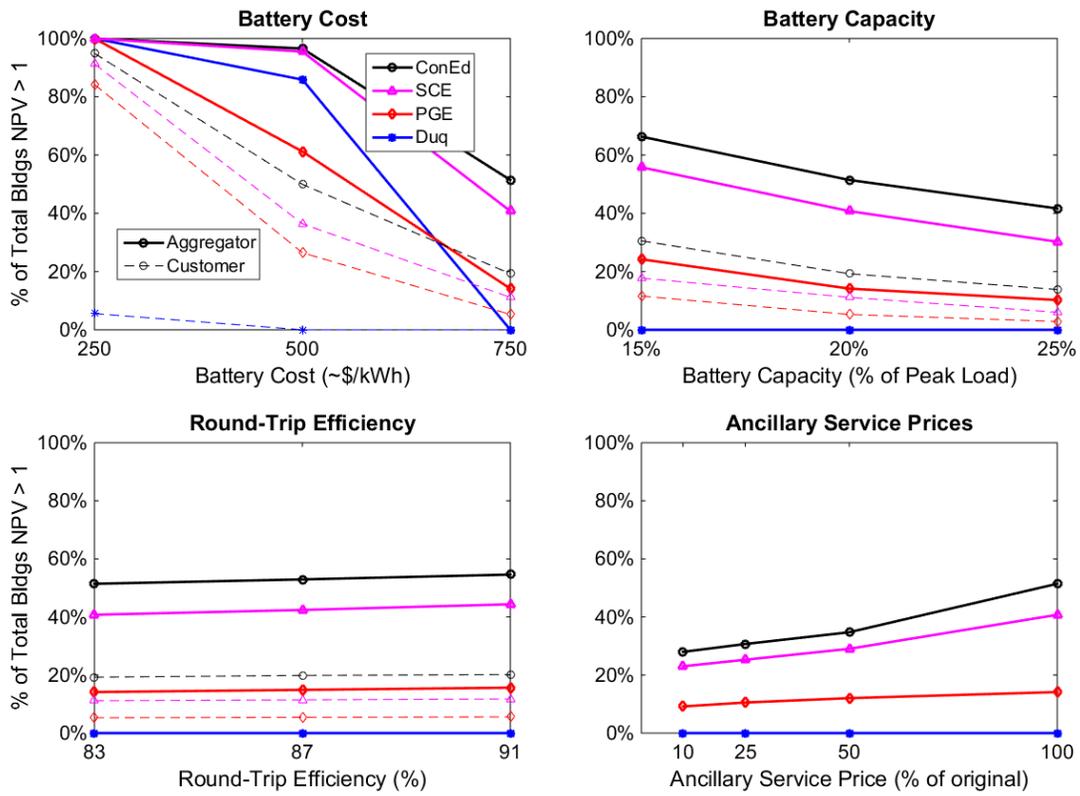


Figure S.14. Sensitivity of economic results to battery characteristics and market conditions.

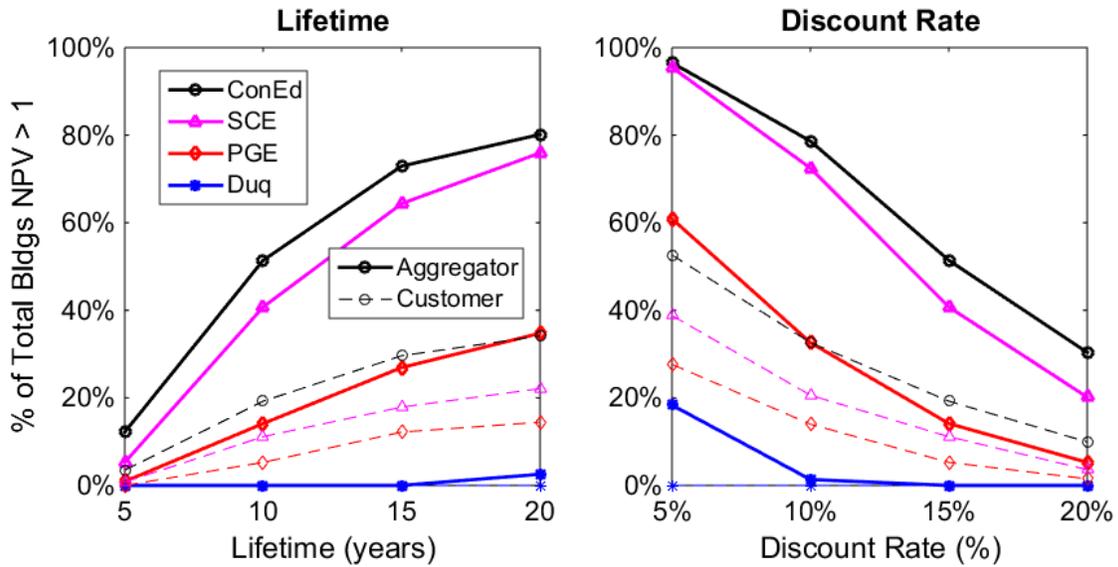


Figure S.15. Sensitivity of economic results to financial assumptions.

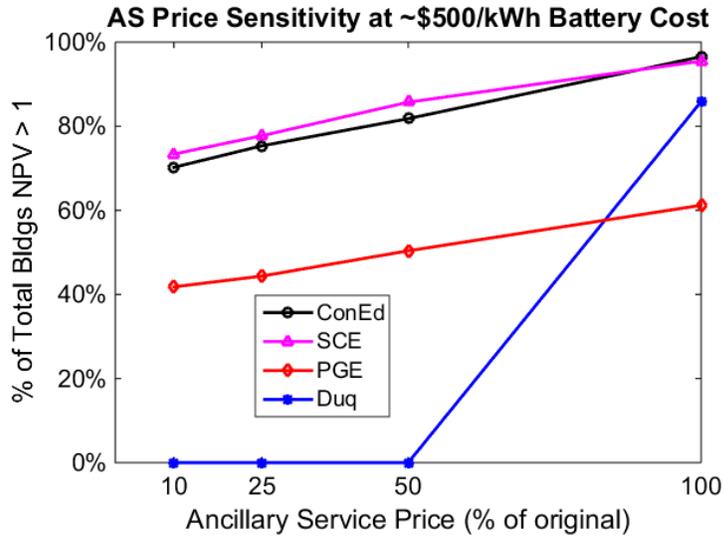


Figure S.16. Sensitivity of economic results to ancillary service prices when battery cost declines to \$400/kWh + \$267/kW (~\$500/kWh). Duquesne Light is extremely sensitive to ancillary service prices because a large proportion of battery revenue is derived from frequency regulation.

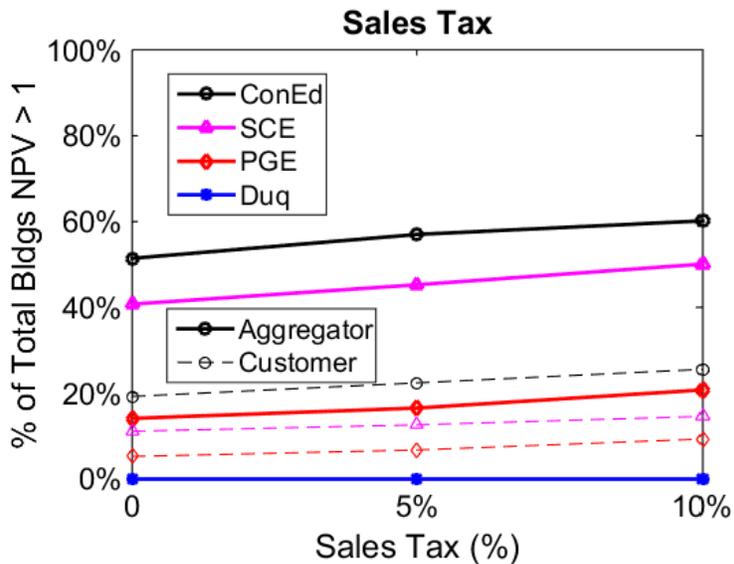


Figure S.17. Effect of sales tax on project economics. Sales taxes are assessed on customer energy bills. The consideration of sales tax improves project economics because batteries lower

total energy bills, and therefore taxes. The main article does not consider sales taxes for ease of comparison across utility tariffs.

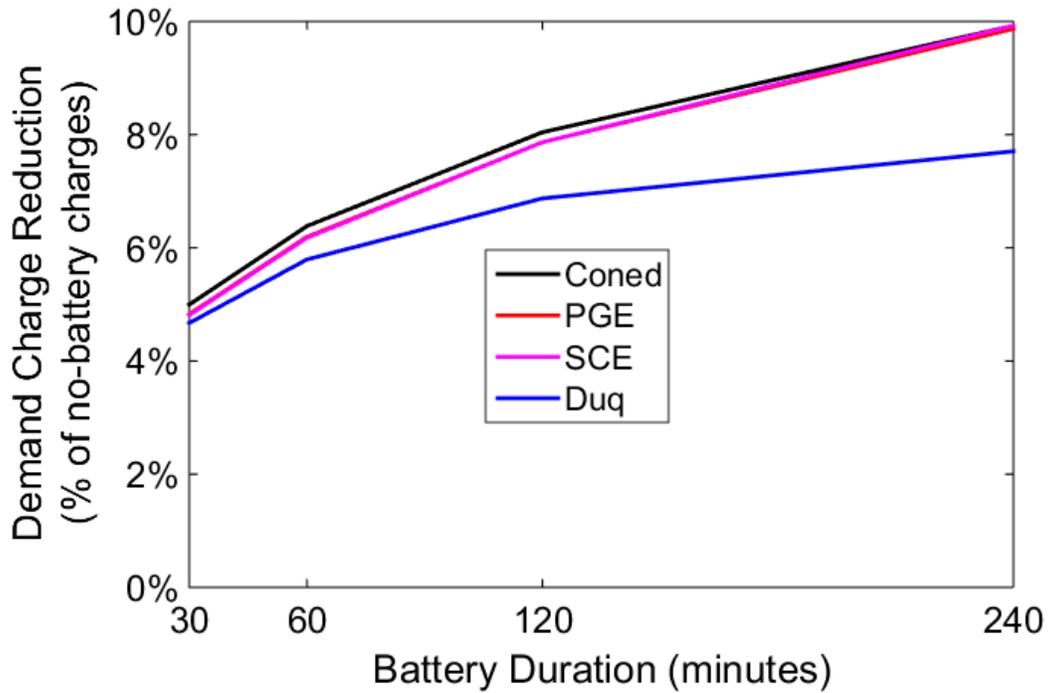


Figure S.18. Demand charge reduction under aggregator ownership across different battery durations. Aggregators are able to mitigate 6% of demand charges with a 60-minute battery sized to 20% of peak load while increasing customer energy costs by only 0.1%.

S5.3 Persistence Forecast Results

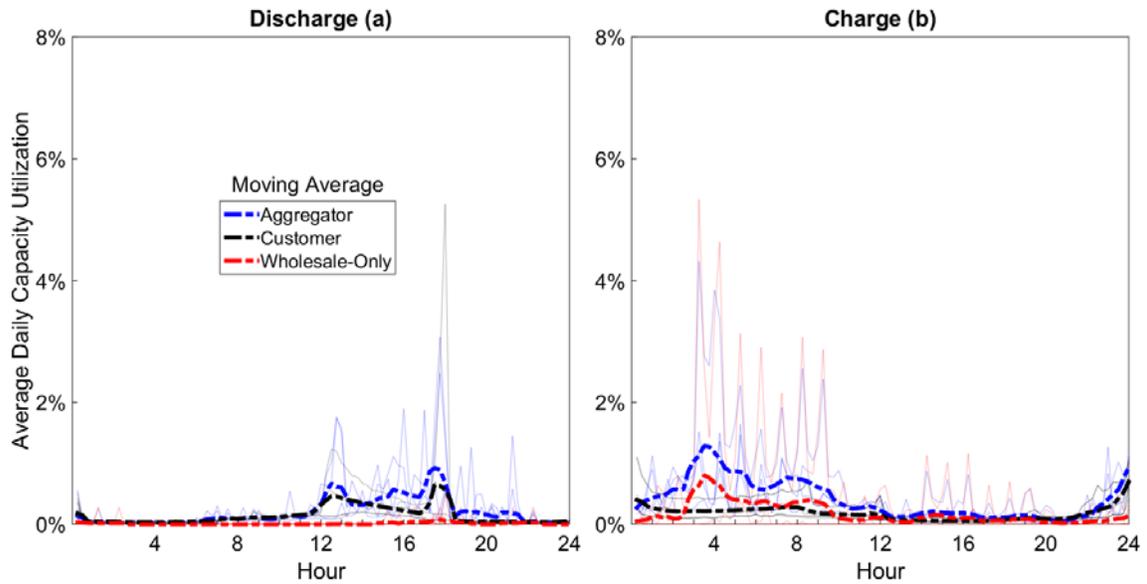


Figure S.19. Average daily discharging (a) and charging (b) profile of battery fleet under perfect forecasts. Light solid lines are individual profiles for each ownership perspective and utility region. Heavy dotted lines represent an hourly moving average of all utility regions for a particular ownership perspective. Average capacity utilization is lower than in perfect forecast scenarios because the persistence algorithm does not forecast peak loads accurately, leading to missed load shifting opportunities and thus fewer profitable opportunities to use the battery.

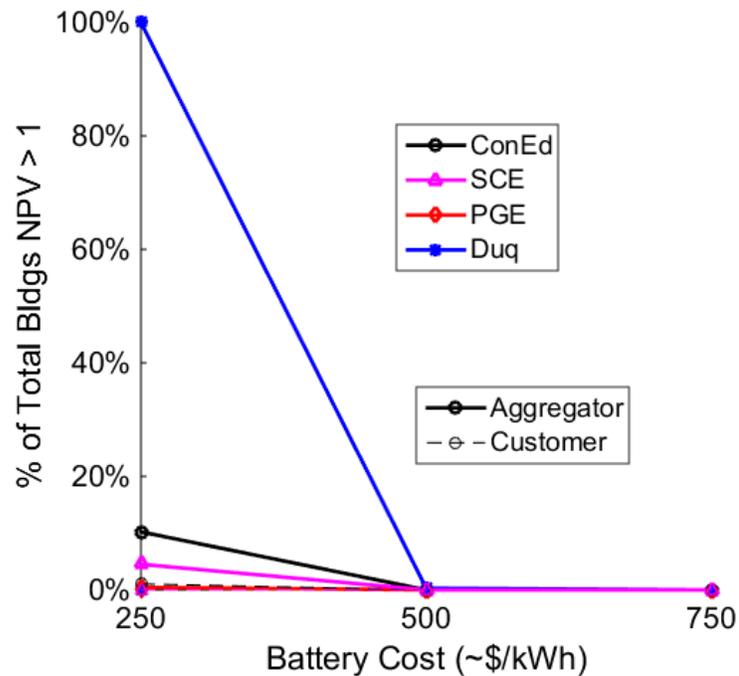


Figure S.20. Sensitivity of economic results to system cost under persistence forecasts.

In all other parameter scenarios, there are no buildings that have $NPV > 1$.

S6. References

- (1) Itron. *2013 SGIP Impact Evaluation*, 2015. Pacific Gas & Electric. <http://www.cpuc.ca.gov/General.aspx?id=7890>.
- (2) 137 FERC 61064. *Frequency Regulation Compensation in the Organized Wholesale Power Markets*, 2011. <https://www.ferc.gov/whats-new/comm-meet/2011/102011/E-28.pdf>.
- (3) Peterson, S. B.; Apt, J.; Whitacre, J. F. Lithium-ion battery cell degradation resulting from realistic vehicle and vehicle-to-grid utilization. *J. Power Sources* **2010**, *195* (8), 2385–2392.

- (4) PJM RTO Regulation Signal Data. <http://www.pjm.com/markets-and-operations/ancillary-services.aspx> (accessed Jan 10, 2015).
- (5) Choi, S. S.; Lim, H. S. Factors that affect cycle-life and possible degradation mechanisms of a Li-ion cell based on LiCoO₂. *J. Power Sources* **2002**, *111* (1), 130–136.
- (6) Broussely, M.; Herreyre, S.; Biensan, P.; Kasztejna, P.; Nechev, K.; Staniewicz, R. . Aging mechanism in Li ion cells and calendar life predictions. *J. Power Sources* **2001**, 97-98, 13–21.
- (7) Eberhard, M. A Bit About Batteries. <https://www.teslamotors.com/blog/bit-about-batteries> (accessed Jan 1, 2016).
- (8) 139 FERC 61130. *Order on Compliance Filing*, 2012. Washington, D.C. <https://www.ferc.gov/whats-new/comm-meet/2012/051712/E-4.pdf>.
- (9) Kaun, B.; Chen, S. *Cost-Effectiveness of Energy Storage in California: Application of the EPRI Energy Storage Valuation Tool to Inform the California Public Utility Commission Proceeding R. 10-12-007*, 2013. Palo Alto, CA. <http://www.epri.com/abstracts/Pages/ProductAbstract.aspx?ProductId=000000003002001162>.
- (10) Towns, J.; Cockerill, T.; Dahan, M.; Foster, I.; Gaither, K.; Grimshaw, A.; Hazlewood, V.; Lathrop, S.; Lifka, D.; Peterson, G. D.; et al. XSEDE: Accelerating Scientific Discovery. *Comput. Sci. Eng.* **2014**, *16* (5), 62–74.
- (11) Siler-Evans, K.; Azevedo, I. L.; Morgan, M. G. Marginal Emissions Factors for the U.S. Electricity System. *Environ. Sci. Technol.* **2012**, *46* (9), 4742–4748.

(12) Siler-Evans, K.; Azevedo, I. L.; Morgan, M. G.; Apt, J. Regional variations in the health, environmental, and climate benefits of wind and solar generation. *Proc. Natl. Acad. Sci.* **2013**, *110* (29), 11768–11773.